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A GENERALISED FRAMEWORK FOR MODELLING & FORECASTING SHARE PRICES

A Field Study on Modelling and Forecasting the Share Prices from the Banking Sector

By

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Certificate of Research

This is to certify that, except where specific reference is made, the work described in this thesis is the result of the candidate's research. Neither this thesis, nor any part of it, has been presented, or is currently submitted, in candidature for any degree at any other University.

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ABSTRACT

Modelling and forecasting the stock market remains a challenge because of the high volatilities in individual stock prices and the market itself. Hence, this topic has received much attention in the literature since forecast errors represent the systematic risk faced by investors. Therefore, the ability to reliably forecast the future values of the shares would provide essential help in reducing that risk to those investors.

The main aim of this research is to develop and calibrate a framework that can be used to model the daily share prices of the companies from the banking sector and hence produce informative and reliable one step-ahead forecasts using an adaptive BPNN. To this end, a novel forecasting algorithm is proposed. This algorithm proposes six steps that, when followed, possibly will lead to obtaining superior forecasting models for the share prices from the banking sector. In addition, novel technical indicators, and further information reflecting market knowledge were developed in this research so as to improve the modelling and forecasting share prices for the banking sector, alongside a novel application of the correctly identified turning points which provided an accurate assessment of the performance of the forecasting models. Furthermore, a selection of a set of inputs that are salient to financial data was identified. The research was to inform and improve share price forecasts of the banking sector.

The historic open share prices for HSBC, Lloyds TSB, RBS and Barclays were used as case studies and the results give evidence to conclude that useable forecasting models can be obtained by employing the developed framework to the share prices from the banking sector in terms of the correctly identified turning points and the direction of the shares which are achieved more than 70% of the time. The empirical results show that using the market knowledge as input generally improved the modelling and forecasting of the share prices from the banking sector.

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List of Acronyms

BPNN	Back-propagation Neural Network
TPs	Turning Points
BTPs	Binary Turning Points
BTP_t	Binary Turning Points at time *t*
TTPs	Type of Turning Points
TTP_t	Type Turning Points at time *t*
OMSs	Ordinal Market Sentiments
OMS_t	Ordinal Market Sentiments at time *t*
NX	Sensitivity of Predicted Maxima Turning Points
PX	Specificity of Predicted Maxima Turning Points
NN	Sensitivity of Predicted Minima Turning Points
PN	Specificity of Predicted Minima Turning Points
NP	Sensitivity of Predicted 'Not Turning Points'
PP	Specificity of Predicted 'Not Turning Points'
DoS	Direction of the Shares

CHAPTER 1

INTRODUCTION

1.1 Background

The stock market suffers high volatility(1) in its prices. This is because of the relatively high number of factors that may significantly influence prices in the market. These factors include, for example, company performance, management, strategic plan, economic factors, changing political climates and interest rates in general (Chatfield, 1996; Claessen and Mittnik, 2002; ASX, 2003; Rahou, 2004). These are introduced later in Section 1.2.

Many investors (either as individuals or companies) are inclined to invest in the stock market, in particular, in shares which are a part of a company ownership. This is because greater returns compared to the other forms of investments, such as currencies and bonds, can be obtained from the shares as they provide regular income through dividends as well as the potential of increasing the value of these shares in the market (Gough, 1997; ASX, 2007).

Because of future uncertainty in the variability of the share prices, many investors attempt to forecast future share price changes by observing the market closely. Hence, the ability to reliably forecast the future values of the shares would provide essential help in reducing the risk to the investors. Hence, any reliable share price

(1) Volatility is defined as an unsystematic change of certain values over a period of time. It is considered one of the most important factors that the investors should take into consideration when evaluating the market (Engle, 1993; Laws and Gidman, 2001).

forecasting method would be beneficial to investors as it would help them in making better investment decisions.

The term 'forecasting' refers to the prediction of future data values based upon historical data and/or descriptive factors, for example, market information. Forecasting can be categorised in two distinct application fields. The first one is Univariate analysis which involves the modelling of data values using either a single input or as a function consisting of explanatory variables, i.e. transfer function. The second application field is Multivariate analysis which involves the modelling of various time series datasets, as inputs, by computing the interaction of each series with one another, hence resulting in the modelling and forecasting of each time series dataset involved (Chatfield, 1996; Makridakis *et al.*, 1998).

This research focuses on Univariate forecasting due to the usage of the historic data and financial market events as inputs to generate a single output which is the future share price for one step-ahead.

Forecasting share values has the potential for numerous benefits (Makridakis *et al.*, 1998). These include:

1. Reducing the required time to make an investment decision on which company to invest.

2. Predicting with the degree of certainty where the market is likely to move in the future which leads to the investors making better decisions about their funds.

There are three established methods which can be used to model future market fluctuations (Baynes, 1973; Firth, 1977; Farnum and Stanton, 1989; Claessen and Mittnik, 2002). These are as follows:

1. Examining the company's activities in order to outline a conclusion (expectation) about its general performance that directly determines market volatility. In other words, examining all available market information, such as

the historic and present financial statements, and the future prospects of the company.

2. Using the market events to estimate the future values of the shares. These events represent the factors that drive the share prices up or down, introduced later in Section 1.2. They are interplay of information and announcements which are related to, for example, the company's performance, company's strategies, economy, political environment, and financial analysts' reports.

3. Predicting the future values from previously available data. In other words, forecasting future share prices which depend on the analysis of the historic share prices by using technical analysis(1).

The choice of implementation of these methods often depends on circumstantial factors surrounding the forecasting. These factors include the available time provided to the forecaster, the type of information available, and the analyst's skills and experience (Firth, 1977; Chatfield, 1996).

Traditionally, each method, outlined above, is separately used to forecast the prices in the stock market. However, in this research, the combination of all these methods was conducted to forecast the future share prices of the banking sector. This is because the forecasting analysis techniques, discussed in point 3 above, solely depend on the historic share prices, this may not provide sufficient ground to build improved financial forecasting models since the share prices are generally influenced by the market events. Therefore, market knowledge, which falls within points 1 and 2 above, was used as an additional input when building the forecasting models. It is conjectured that this will provide an improved understanding and forecast of the underlying dynamics of share prices of the banking sector.

As previously mentioned, there are several factors which influence the variability of the share price positively or negatively in the market. These factors are introduced in the following section.

(1) Technical analysis is the use of the mathematical and computational models to forecast the future values by analysing historic data.

1.2 Factors Affecting Share Prices

A number of factors occur on a daily basis that may lead, directly or indirectly, to an increase or decrease the companies' share prices in the market. However, these share prices are governed by the principle of *supply and demand*[1]. This principle, and hence the selling or buying buys of the shares, is in turn dictated by the key factors, discussed below, followed by a synthesis of the complexities of forming judgments on the influence these factors have on share prices in the real world.

1.2.1 Company Performance

The performance of the company, as defined by the financial advisers, is an indication of the investment security (Vass, 1987). The share price, as a general rule, depends significantly on information related to the company performance, where it is general understood that good performance leads to an increase in the share price and vice versa (Firth, 1977; Rao and Radjeswari, 2000; O'Regan, 2006). In general, degradation of the performance of any company leads to decreasing the investment in this company, i.e. decreasing the demand on the shares, and hence this lead to a decrease in the price of the share.

A combination of several factors can be used to evaluate the performance of the companies on a daily basis. These include the financial performance, management, and strategic plans, which are introduced in the following sections.

1.2.1.1 Financial Performance

Financial performance, as defined on the Investopedia website, is a result of the management of the company's assets to generate revenues. It is an essential factor which affects the share prices (Firth, 1977; Neely *et al.*, 2001; O'Regan, 2006). This performance is usually evaluated by the financial experts in terms of the corporate financial report whether it is quarterly, half-yearly or annually.

(1) Supply and demand is one of the fundamental theories of economics of the market value wherein, in this research, share price is determined by the interaction of opposing seller and buyer forces. If there is a high demand for shares (i.e. low supply), this leads to an increase of the share prices while a low demand (i.e. high supply) leads to a decrease the share prices.

Nevertheless, in this research, the information provided in these reports was utilised as daily events used in forecasting.

For example, Barclays Bank Plc. reported on 20th February 2007 their annual profit for the financial year 2006 as £7.14bn which saw an increase in its share price.

1.2.1.2 Management

The quality and strength of the company's management affect the investors' decision when evaluating the company and hence can affect its share price in the market (Neely *et al.*, 2001; ASX, 2003). Under normal market condition, the quality and the strength of the company's management lie in the directors of the company, and any change here may cause a positive or a negative reaction to the share price.

This happened with the Royal Bank of Scotland and the Islamic Bank of Britain when they announced, on 21st April 2005 and 29th September 2005 respectively, a change of director. This led investors to hold (no selling or buying), since the new directors are not known by the shareholders, until they are sure that these directors are the right persons for this position.

1.2.1.3 Strategic Plans

Another determinant that is considered part of the company performance is the strategic plan of the company. The future plans of the company can affect the share price positively or negatively (Neely *et al.*, 2001) depending on the expected benefits for the company's shareholders.

For example, HSBC Bank Plc. agreed, in the first week of February 2005, to sell its building in Singapore and subsequently leased it for a period of seven years. This agreement positively affected the share price. Another typical example took place on the 18th September 2008 when Lloyds TSB finalised a deal to buy the shares of HBOS (Halifax-Bank of Scotland) for £12.2bn and, hence, that led to an expected increase of the earnings before tax of £1bn a year in 2011. This agreement had a positive effect on the share price of Lloyds TSB.

1.2.2 Competition

The domestic and international competition between same sector companies usually affects the share price (Rappaport, 1997). This occurs when any company competes against another company in its products which probably affects the supply and demand of the shares and hence affects their prices.

This is what happened when Lloyds TSB Bank offered on 15th February 2005 a personal bank account consistent with Islamic Sharia Law, a product similar to one usually provided by Islamic Bank of Britain. This arrangement affected share price of the Islamic Bank of Britain negatively.

1.2.3 The Economy

Investors take into consideration the economy when making a decision about their investment is economic conditions. This is because the share prices are related to the economic condition (Schwert, 1990a; Cheney and Moses, 1992). Economic conditions are usually affected by a number of variables (Cheney and Moses, 1992; Rao and Radjeswari, 2000). These variables include, for example, the following:

- Inflation which potentially affects in its turn, for example, nominal cash inflows, interest rates, and exchange rates.
- Industrial production would influence the profits of the companies and hence the dividends.
- Currency fluctuation which influences the foreign investments.

Generally, the economy, either nationally or internationally, affects the investors' decision. A good economy encourages the investors to invest their funding in the stock market and, hence, this leads to increasing the demand which possibly causes the share prices to increase.

1.2.4 The Politics

Political factors can have a direct impact on the market (Heri and Rossi, 1994). This factor affects the everyday operation of the stock market and can come in the form of policy or legislation change concerning, for instance, the statutory minimum wage and taxes which affect the businesses, positively or negatively and hence can affect share prices.

As a general rule, the politics of any country attract or repel the investors and this affects the supply and demand amount of the shares and, thereafter, the prices in the market.

1.2.5 Interest Rates

Share prices are generally affected by the changes in interest rates (Cheney and Moses, 1992; Heri and Rossi, 1994; Gough, 1997), as shown in the following examples:

- When the interest rates rise, the investors will be reluctant, in most cases, to invest and will prefer to keep their funds as savings, bonds and other secure interest-bearing instruments (Heri and Rossi, 1994; Gough, 1997). This often leads to a decrease in the supply and a decrease in the demand on the investment in the shares which generally lead to falling in the price of shares, and vice versa.

- When the interest rate changes, the economy, as mentioned earlier, will be affected (Cheney and Moses, 1992) and hence that will possibly affect the share price variability in the market, as earlier discussed in Section 1.2.3.

1.2.6 Analysts' Viewpoints

Analysts investigate companies' activities and write reports on their findings. These analysts often become experts on the companies they analyse through learning the business, studying the industry, reading trade publications, and so on. In addition, they are often in personal contact with corporate officials as they analyse the conditions inside and outside the companies (Brown and Bentley, 1997). Hence, the analysts' reports affect:

- Investors' decisions about their investment in the companies.
- Investors' trends to buy or sell the shares of the companies.

These in turn affect shares by causing an increase or a decrease in their values in the market.

1.2.7 Market Sentiment

Market sentiment is the general feeling about investment which is related to the expected price movement of the stock market. It is an important factor that drives the share price in the stock market (Yu and Tam, 2007). When the market sentiment refers to a rise in share prices, the market is known as a "bull market(1)", while when it refers to a fall in share prices, it is known as a "bear market(2)" (Vass, 1987). However, it is difficult to determine the market's progression using this factor. This is because the market sentiment is the summation of a variety of factors including the all previously mentioned factors above. In this research, the market sentiments were developed to be used as input, as discussed later in Section 3.2.2.

Typical examples of this factor are the collapse of one of the largest investment banks in USA, the Lehman Brothers Inc., in September 2008 and the global banking system in October 2008, which generally had a negative effect on the share prices of the UK's banking sector.

It is worth noting that the direction of the shares is the effect of a combination of the simultaneous influences of the various factors mentioned above. Thus, for instance, the combination of these factors can either cause the share prices to be

(1) A bull market refers to an augmentation of the share prices in the market which leads to increasing the investors' confidence to buy the shares.

(2) A bear market refers to a reduction of the share prices in the market which leads to decreasing the investor's confidence to buy the shares.

static (i.e., each factor cancel each other out) or cause the share prices to rise or fall (i.e., predominance of a positive or negative factor). For example, the reduction of the interest rates globally on the first week of October 2008 did not drive the share price up which is usually the case, as addressed in Section 1.2.5. This is because the economic crisis which happened at that time forced the share prices to remain low.

The key factors above were used in this research to determine an input when building the forecasting model. It is expected that will help to improve one step-ahead share price forecasts of the banking sector.

1.3 Aim and Objectives of the Research

In spite of the concerns that share prices can not be modelled due to their ability to follow unpredictable movements (see for example Taylor, 1986; Chatfield, 1996; Chatfield, 2000), the main aim of this research is to develop and calibrate a framework that can be used to model and forecast the daily share prices of the companies from the banking sector.

This research aim to:

- Develop a forecasting algorithm that can be applied in modelling and forecasting financial time series.

- Develop an accuracy measure specific to financial forecasting, namely the correctly identified turning points, in addition to the existing accuracy measures to evaluate the performance of the financial forecasting models. The objective is to find suitable accuracy measures that can be used to select the most reliable financial forecasting models.

- Empirically examine the performance of the Back-propagation Neural Network (BPNN) in financial forecasting in comparison with other established approaches such as Random Walk[(1)] and GARCH[(2)].

- Empirically examine the effect of the existing types of input data on forecasting models and development of two technical indicators that can be used as input which are salient to financial data and hence can inform and improve the share price forecasts of the banking sector. The objective is to identify a suitable set of inputs that explains the output positively.

- Include the market knowledge as an input when building a forecasting model in order to improve share price forecasts for the banking sector.

It is expected that the results of this research will be of benefit to investors and academics alike.

1.4 Research Scope

The scope of this research is to:

- Model the daily opening share prices of the banking sector, which usually suffer high volatility in their movement, to produce one step-ahead forecasts.

- Improve share price forecasts using two novel technical indicators, developed in this research, and market knowledge as inputs when building the financial forecasting models.

- Improve the selection of an adequate financial forecasting model using an accuracy measure, developed in this research, which is suitable to evaluate the financial forecasting models.

- Forecast accurate values of the shares using a BPNN.

[(1)] Random Walk, usually denoted by RW, is a mathematical model used for modelling time series to examine whether the share prices follow random movements or not

[(2)] GARCH, stands for Generalised AutoRegressive Conditional Heteroskedasticity, is a non-linear statistical forecasting model which was developed by Bollerslev (1986).

- Build forecasting models which deal with the market under normal conditions.

Should the points above be successful, this will allow the construction of a superior forecasting model which will minimise the risk of the investment in the stock market, in particular, when dealing with shares. In addition, the modelling approach discussed in this research can be implemented as a general forecasting framework to be utilised in any financial application field.

1.5 Research Methodology

The quantitative method suits the needs of this research due to the nature of the employed data. In order to investigate the volatility of share prices, the banking sector was chosen as a case study, in particular, the share prices of HSBC, Lloyds TSB, the Royal Bank of Scotland and Barclays. These banks were chosen since they are global banks and their shares are held by a large number of shareholders and are regularly traded.

Two sets of data were utilised in this research to model and forecast the share prices from the banking sector outlined above. These data consist of the following:

1. Historic opening share prices of the specific banks.

2. Market knowledge which represents the daily events affecting share prices in the banking sector. In the modelling and forecasting of the share prices, this information was used as an input, in addition to the historic share prices, which is expected to help improve the share price forecasts.

A BPNN, which is an established non-linear mathematical forecasting method, was used in this research for modelling and forecasting the future share prices of the banking sector. This is because this approach is well established in the field, especially in business and financial application (Kong and Martin, 1995; Chatfield, 1996; Lawrence, 1997; Gradojevic and Yang, 2000; Yao *et al.*, 2000; Hamid, 2004). In addition, statistical approaches, such as Random Walk and GARCH

Models, were employed in order to comparatively evaluate the forecasting models obtained using the artificial neural networks.

1.6 Thesis Structure

Chapter two gives the literature review of current financial forecasting applications. Chapter three highlights the input data and develops two novel technical indicators to measure market sentiments and knowledge. Chapter four introduces the methodology that was employed in this research. Chapter five introduces the applications of building the financial forecasting models of the companies from the banking sector. Chapter six gives the results and discussion. Finally, in Chapter seven, the conclusions of the research are outlined and future investigative work is proposed.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The issue of stock market modelling and forecasting has received attention in the finance literature through the last two decades because of high volatility in individual stock prices and the market itself.

This volatility in the stock market prices has generally increased after the stock market crash on the 19th October 1987 and the high drop in the stock market prices which occurred on the 13th October 1989. In addition, other reasons such as, the increase in the trading level in stocks due to popularity of computerised trading in the market (Schwert, 1990a; Schwert, 1990b; Malkiel and Xu, 1999).

Modelling and forecasting the stock market is not a new phenomenon. In the 1930s it was attempted by *Cowles III* (Teweles and Bradley, 1987). *Cowles* examined 16 financial services for 4.5 years. These services showed an annual record gain for the stockholder of on average 1.4% less than the average common stock. In addition, *Cowles* investigated, over the same period, the ability of 24 financial publications to forecast the future stock market. He found that the investigated results in this study were 4% less than the results obtained by the market's experts.

In the 1940s, share prices were forecasted by the Securities and Exchange Commission (SEC) through its study of stock trading on the New York Stock Exchange (Teweles and Bradley, 1987). The market continued downwards and the trend of share prices did not rise again until 1950. The SEC examined 896 different pieces of literature disseminated by 166 investment advisers, brokers and dealers. Of the total of 489 forecasts made on the long-term market outlook at that time, 60% were strongly optimistic, only 4% advised investors to sell at least part of their holdings, and the rest were uncertain.

However, the researchers in the two studies relied only on the analysts' and investors' reports without taking into consideration the market events which represent the factor that affect share prices, previously introduced in Section 1.2.

More recent studies have investigated financial forecasting using different approaches and different input data when building forecasting models. Some relevant previous studies are introduced below.

2.2 Related Previous Studies

Forecasting the stock market remains a challenge for researchers as most studies that have investigated the reliability of technical analysis in forecasting the stock market but have provided little benefit to the easy wealth seeker.

In spite of this, several related studies have received much attention in the finance literature. In this research, some of these studies were discussed in relation to the following points:

1. Examination of market information in forecasting the stock market.
2. Examination of Artificial Neural Network (ANN) approaches and statistical approaches to select a suitable approach for financial forecasting.
3. Development of accuracy measures which help to select an adequate financial forecasting model.
4. Examination of different types of technical indicators to be used as input when building financial forecasting models in order to find the effectiveness of these technical indicators in financial forecasting.

5. Development of an algorithm for building adequate financial forecasting models.

Related previous studies which covered the five points above are introduced in turn below.

2.2.1 Market Information

This section discusses two previous studies that use the financial market information, which are usually published in the media, in forecasting the financial market. These are introduced below.

Kohara *et al.* (1997) investigated forecasting the daily Tokyo Stock Price Index (TOPIX) using the BPNN. The input data which was used consisted of the financial market information, used as economic indicators, in addition to the time series of the daily prices of Tokyo Stock Index. The financial market information, described in this study as a prior knowledge, was extracted from newspaper headlines. This consisted of, for example, the exchange rate of the Yen against the American Dollar, the interest rates and the crude oil price. The results show that the stock market forecasts obtained by using the market information were better than the forecasts obtained without market information.

In a similar study, Wuthrich *et al.* (1998) developed a technique to forecast Asian, European, and American stock market indices using the daily financial market information which is already published on the World Wide Web. This information includes the financial analysis report and what happened in the world related to the stocks, currencies and bonds. The results show that using the new daily market information in addition to historic index values, which includes the old index values and the dated market's news, improved the stock market's forecasts.

As shown in the two previous studies above, the market knowledge improves the financial forecasting when it is used as an input in building the forecasting models. The market knowledge represents all of the factors that affect prices in the market, as introduced in Section 1.2, as these factors usually drive the prices in the market up and down. Despite the fact that some studies state that useful forecasting models can be made without any market knowledge (see, for example, Yao and Poh, 1995; Yao *et al.*, 1997; Yao and Tan, 2000), it is believed that using the market knowledge as input might improve the share price forecasts for the companies from the banking sector. Therefore, the market knowledge was used in this research as input, in addition to the historic share price time series, when building the financial forecasting models, as introduced later on in Section 3.3.

2.2.2 Forecasting Approaches

Several forecasting approaches have been examined in previous studies for modelling and forecasting the financial time series. In this section, a number of these studies, which were published in the finance literature, were discussed starting with the studies used the BPNN, as shown below.

Yao *et al.* (1999) investigated forecasting the daily stock prices for the Kuala Lumpur Stock Exchange Composite Index (KLSE) using BPNNs and ARIMA models. The same data of the above study were used to forecast the future stock prices of KLSE. The results show that the BPNN Model was superior compared to ARIMA Models since, it was expected, ARIMA Models are linear models while Neural Networks are non-linear models which are more suitable for forecasting the financial time series.

Yao and Tan (2000) investigated forecasting exchange rate movements for the American Dollar against the Japanese Yen, Deutsche Mark, British Pound, Swiss Franc, and Australian Dollar using the BPNN and ARIMA Models. Historic exchange rates from 18th May 1984 until 7th July 1995 were analysed to forecast the future rates. Many forecasting models were built in this study using different types of inputs such as normalized data and moving average. The study found that the BPNN was superior to ARIMA Models in terms of the accuracy measure Normalised Mean Square Error (NMSE).

Gradojevic and Yang (2000) show that providing good quality results of high frequency Canada/US exchange rate forecasts could be achieved using the BPNN. This study concluded that the BPNN consistently performed better than other approaches, such as random walk and any linear models, for the various out-of-sample forecasts in terms of the Root Mean Square Error (RMSE).

Yao *et al.* (1997) investigated forecasting the exchange rate of the Swiss Franc (CHF) against the American Dollar (USD) using the BPNN. The results show that the BPNN provides an adequate financial forecasting model.

Gately (1996) presented in his book "*Neural Networks for Financial Forecasting*" a developed forecasting model to predict the future values of S&P-500 stock index using a BPNN. This model provided admirable results, in terms of the Mean Absolute Percentage Error (MAPE) which was 0.30, and was validated to be used as a benchmark for further improvement in this book. Hence, the results of this model were used as a benchmark in the present research. However, are the conventional accuracy measures sufficient to decide on the adequate financial forecasting model for forecasting the share prices from the banking sector?

The previous studies, introduced above, examined the Back-propagation Neural Network (BPNN) in modelling and forecasting the financial times series and showed that it was generally successful, as further affirmed by, for example, Yao and Poh (1995) and Yao and Tan, 2001a. In addition, other approaches, in particular statistical approaches, were examined in several studies, listed below, for modelling and forecasting the financial times series. Some of these are introduced in turn below.

Karmakar (2004) examined a variety of GARCH modelling to forecast the volatility of future monthly prices of S&P CNX Nifty Index using 3076 observations from 1st January 1991 until 31st December 2003. It was found that the standard GARCH Model, GARCH(1,1), outperformed other models in terms of forecast errors such as Mean Error (ME), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

Husain and Uppal (1999) examined the volatility of stock returns of 36 companies, covering the period from 1st January 1989 until 30th December 1993, in the Pakistani Stock Market using ARCH and GARCH Models. Numerous models were built and it was found that GARCH(1,1) fits the majority of datasets used in this study in terms of forecasts errors.

In addition to the above studies, another study shows that the GARCH(1,1) provides a good fit for high volatility stock return and superior forecasts of market volatility (see, for example, Akgiray, 1989; John, 2004) as compared to other statistical forecasting. Therefore, the GARCH(1,1) model will be investigated in this research as an initial modelling step for the share prices of the banking sector. The following studies explore the implementation of the GARCH model using various parameters, alongside the implementation of the ARIMA modelling approach.

McMillan *et al.* (2000) investigated the forecasting of the daily closing prices of FTSE-100 and FTA all shares index using GARCH Models. It provided a comparative evaluation of the volatility forecasting ability of GARCH models, Threshold-GARCH (TGARCH), Exponential-GARCH (EGARCH) and component-GARCH models (CGARCH). It found that the GARCH models and EGARCH models were better than others. On the other hand, the results generally suggested that the class of GARCH models provided relatively poor volatility forecasts.

Balaban (2004) tested the symmetric (ARCH and GARCH) and asymmetric (GJRGARCH and EGARCH) conditional variance models to forecast the monthly exchange rate of the American Dollar (USD) against Deutsche Mark. The historic exchange rates which covered 24 years from 2nd January 1974 until 30th December 1997, which represent a set of daily averages of closing bid-ask prices of the American Dollar-Deutsche Mark (FX_t), were used and obtained from the Deutsche Bundesbank. It was found that the symmetric GARCH model provides relatively good forecasts of monthly exchange rate volatility compared to other models.

Rahou (2004) investigated the use of ARIMA Models to analyse historic close share prices from the 1st September 2002 until 31st August 2003 for five banks. The overall results provided evidence that share prices movements were either non-linear or random. Therefore, ARIMA Models failed to forecast future share prices. Hence, the study concluded that this approach was not capable of modelling the volatile share prices.

Alsaleh (2002) investigated forecasting exchange rates for two major international currencies, British Pound (GBP) and US Dollar (USD), against the Kuwait Dinar using the Box-Jenkins approach (ARIMA Models). The daily exchange rates covered the period from 1st January 1996 until 22nd February 1999 and the economic factors, were used to build the forecasting model. The results show that the ARIMA models used were not sufficient for financial forecasting.

The overall results of the above studies generally demonstrate that the Artificial Neural Network approach, in particular the BPNN, outperforms traditional statistical modelling techniques in financial forecasting. Thus, the BPNN was used in this research as the main approach to forecast the future daily share prices of the banking sector. In addition, ARMA with GARCH errors model was used to make a comparison to the BPNN as it is more effective than other statistical approaches, such as ARIMA Models, in financial forecasting.

Furthermore, some studies (see for example, Chatfield, 1996; Chatfield, 2000; Taylor, 1986) argued that time series could follow some random pattern which fails to be modelled using traditional techniques. Nevertheless, Fama (1965) and Hasan (2004), for example, demonstrated that certain time series exhibited random movements, whilst other studies (Taylor, 2000; Yu, 2002) refuted this claim. To this end, the Random Walk (RW) Model was used to investigate whether the time series used in this research follows a random movement or not and thus used as a benchmark approach.

2.2.3 Accuracy Measures

In order to improve the forecast-ability of the financial time series, several studies (see for example, Yao and Poh, 1995; Hyndman and Koehler, 2006) developed accuracy measures which might be suitable to evaluate the performance of the financial forecasting models and hence aid in selecting adequate forecasting models that are suitable for financial forecasting.

Yao and Poh (1995) presented two accuracy measures to evaluate the financial forecasting models. These were the Signs and Gradients of share prices. The Sign measures the correctness of signs between the actual data and forecast data after normalisation. The Gradient measures the correctness of the direction between the actual data and forecast data.

Hyndman and Koehler (2006) developed a new accuracy measure, namely the Mean Absolute Scaled Error (MASE), which scales each forecast error at time t in the time series using, for example, the Mean Absolute Error (MAE) as a denominator. The authors state that this accuracy measure is effective in evaluating the performance of forecasting models generated for intermittent time series. In addition, this new accuracy measure provides a comparison ground for further forecasting models.

The *Gradient* measure which was presented by Yao and Poh (1995) helps to identify a correct trend of the time series. It is expected that this measure is more decisive to investors than other measures presented in the two studies above. Therefore, this measure was used in this research to evaluate the performance of the financial forecasting models. However, using the *Gradient* measure in addition to conventional accuracy measures, such as RMSE and MAPE, is still not sufficient for evaluating the performance of the financial forecasting models of the share prices. This is because these measures fail to correctly identify the actual turning points in the modelling of the time series. Therefore, another accuracy measure, which is the correctly identified turning points, was developed to be used in this research to evaluate the forecasting models, as presented later on in Section 4.6.1.7. Although the MASE measure has proven to be most effective according to

Hyndman and Koehler (2006), its implementation is not relevant in the present research. This is because this accuracy measure can be used upon intermittent time series (see for further discussion Hyndman (2006) in Foresight Journal) and the time series used in this research is a continuous time series.

2.2.4 Technical Indicators

A number of previous studies have examined the technical indicators, defined later in Section 3.2, as input when building the forecasting models. Below are two of these studies, chosen as an example, which examined several technical indicators as inputs.

Yao and Poh (1995) examined five technical indicators to be used as inputs in forecasting the daily stock prices of Kuala Lumpur Stock Exchange Composite Index (KLSE) using BPNNs. These technical indicators were Moving Average (MA), Momentum (M), Relative Strength Indicator (RSI), Stochastic (%K) and the Moving Average of Stochastic (%D). The results show that the technical indicators MA, M, and RSI were appropriate in building an adequate financial forecasting model while %K and %D did not significantly improve the forecasting model. However, the study's report does not mention which method was used to calculate the moving average, whether it was a centred moving average or a prior moving average, and which period was used to calculate the RSI.

In a later study, Klassen (2005) investigated six technical indicators to produce one step-ahead forecasts of the NASDAQ and Dow Jones stock prices using a Feed-forward Neural Network. These indicators were the Relative Strength Index (RSI), Moving Average (MA), Change in Moving Average, Exponential Moving Average (EMA), Change in Exponential Moving Average, Moving Average Convergence/Divergence (MACD), and Rate or Return of Stocks (RRS). The results show that using the MA, Change in MA, EMA and Change in EMA in addition to historic values improved the stock price forecasts comparing with other technical indicators used in this research.

In spite of the success of some of the technical indicators as inputs when building the forecasting models in the empirical studies as shown, for example, in the two previous studies above, it is conjectured that these technical indicators are not sufficient for financial forecasting as they do not identify the turning points and the intensity movements of the time series which may help to improve the share price forecasts of the banking sector. Therefore, two technical indicators were developed during this research providing the turning points and the intensity movements of the time series as introduced in Section 3.2.

2.2.5 Forecasting Algorithms

As there is no standard procedure or technique that can be used to model and forecast financial time series, several studies proposed an algorithm that can be followed when modelling the financial time series and hence improving the financial forecasts. Two previous studies, which were chosen as an example, are discussed below.

Kaastra and Boyd (1996) provided eight practical steps to build financial forecasting models. These steps were: Step 1: Variable Selection, collect suitable inputs that can affect the target positively when building the forecasting model; Step 2: Data Collection, cost and availability are taken into consideration when collecting the data; Step 3: Data Pre-processing, pre-process the data to be used as input in order to increase the quality of the data; Step 4: Training, Testing, and Validation Sets, dividing the time series into three sets, the first one for training the data, the second one for testing the trained model, and the last one for validating the model; Step 5: Neural Network Paradigms, this step determines the architecture of the neural network which includes the number of neurons in each layer (input, hidden, and output); Step 6: Evaluation Criteria, using accuracy measure to evaluate the performance of the forecasting models; Step 7: Neural Network Training; and Step 8: Implementation, forecast the future values using the concluding forecasting models.

Yao and Tan (2001b) proposed an algorithm for building financial forecasting models. This algorithm consists of seven steps which were: Step 1:

Data Pre-processing, prepare the data that are used as input when building the forecasting model; Step 2: Selection of Input and Output variables, collect all the available information that affects the output; Step 3: Sensitivity Analysis, the input that most affects the output to be kept, and the input that has least affected the output will be discarded; Step 4: Data Organisation, collect the available data that is related to the forecasting aim and partition the data into three datasets, the first two parts of data are used to train the model and the third part of data is used to test the model; Step 5: Model Construction, evaluate the forecasting models by using, for example, the profit and time factors in addition to the Least Squares Error (Yao and Tan, 2001a); Step 6: Post Analysis, determine how many times the Neural Network Model should be retrained; and Step 7: Model Recommendations, including some recommendations which have to be followed when building financial forecasting models.

The researchers, in the two studies above, proposed that the forecasting process are carried out in single steps to achieve an adequate forecasting model since there is no standard procedure or technique that can be used for the forecasting process. Although building the financial forecasting models using these proposed algorithms led to improved forecasts of the financial time series under investigation, these proposed algorithms are not sufficient to identify the most adequate financial forecasting model. This is because the algorithms above are unidirectional and do not include feed-back and feed-forward mechanisms to update the input data or the forecasting approach used to build the forecasting model when an insufficient model is obtained. In another words, these algorithms do not allow for the accumulation of knowledge that is not integral feature of the modelling process. Thus, this present research offers a new algorithm which overcomes these limitations. It is expected that following the proposed algorithm will yield superior financial forecasting models.

It is worth noting, each time series is unique and each expert possesses different statistical skills and utilises various forecasting tools and/or software packages to model a given data series. Hence, a prior knowledge of contemporary forecasting techniques is to be investigated by the expert as part of the forecasting process.

Therefore, within the novel algorithm developed in this research, prior information concerning the practicality of forecasting is included as a decision stage which further reinforces the potential of obtaining superior modelling, given any situation. The steps of implementation of this novel algorithm are introduced in detail in Section 4.7.

2.3 Chapter Summary

A review of the precedent studies, which are related to the topic pertinent to this research, was presented in this chapter.

It was found that the BPNN outperformed other approaches in modelling and forecasting financial time series. Therefore, it is used, as a main approach, in this research, in addition to GARCH and Random Walk models which are used in order to make a comparison with the BPNN. In addition, the following will be developed in the course of this research:

1. Two technical indicators, which are salient to financial forecasting, to be used as input since the existing technical indicators were not sufficient for share prices forecasts.

2. The market knowledge input, which is constructed from other factors affecting share prices, as input when building the financial forecasting models. Previous studies show that the market knowledge improves the financial forecasting when it is used as an input.

3. An accuracy measure to evaluate the performance of the forecasting models in terms of the correctly identified turning points. We expect that this measure is significant to the financial forecasting since it provides an evaluation for the model in terms of a point in which the direction of the shares changes.

4. A forecasting algorithm to be followed in modelling financial time series in order to cover the limitations in the algorithms proposed in previous studies.

The following chapter presents the novel input data, developed in this research, which might be suitable to improve the adequacy of the financial forecasting models.

CHAPTER 3

INPUT DATA

3.1 Introduction

The careful selection of input data is an important process in any forecasting application since the performance of the resultant forecasting models depends, amongst other things, on the selection of the input data. However, the preliminary treatments of these input data usually depend on the application field (Tarassenko, 1998). In this research, two innovations which are salient to financial time series, which may consequently inform and improve the modelling and forecasting the share prices from the banking sector, were developed. The first innovation constitutes the implementation and classification of two novel technical indicators, used as inputs when building the forecasting models, which are the turning points and the markets sentiments. The second innovation carried out in this research is the development of a way to measure the market sentiments addressed in the first innovation. These are introduced in the following sections.

3.2 Technical Indicators

In a forecasting context, technical indicators are generally used to assemble a collection of variables by applying some logical and/or mathematical transformations to the data, normally in a time series, to create a single variable that summarises the information in the initial variables. They can be useful in understanding the general movement of the time series and in reducing the dimensionality of the application.

Several technical indicators have been successfully used as inputs in empirical works when building financial forecasting models (see, for example, Klassen, 2005 and Yao and Poh, 1995). Key technical indicators used in financial forecasting include the Relative Strength Index (RSI), the Stochastic (often denoted by as %K), the Moving Average of Stochastic (denoted by as %D), the Exponential Moving Average (EMA), and the Moving Average Convergence Divergence (MACD). These are introduced below.

The Relative Strength Index (RSI) is defined as a measure of the strength of upward versus downward movement of the observations in a given period of the time series (Yao and Poh, 1995; Man-Chung *et al.*, 2000; Klassen, 2005). It measures the ratio of the upward to the downward intensities movements of the share prices which, it is believed, helps to improve the share price forecasts.

The Stochastic (%K) measures the relationship between an observation at time t to the range of the largest and smallest observations in the last n periods of the time series. The moving average of Stochastic, denoted by %D, is often calculated in order to smooth the stochastic technical indicator (Yao and Poh, 1995; Man-Chung *et al.*, 2000). However, this technical indicator, according to the contents of the Forex Strategies Website, could provide wrong signals, i.e. wrong directions for the share price movements, when is calculated for a short term period comparing to a long terms period, which possibly affect the accuracy forecast of the share prices.

The Exponential Moving Average (EMA), sometimes also called an exponentially weighted moving average (EWMA), is a type of moving average technique that gives more weight to more recent, depending on the n period of the moving average. This technical indicator, therefore, provides a quicker response to share price fluctuations than a Simple Moving Average (Makridakis *et al.*, 1998; Pyle, 1999; Klassen, 2005). Similar to the Stochastic, the EMA could also provide wrong signals for the share price movements (Forex Strategies Website).

The Moving Average Convergence Divergence (MACD) measures the difference between two periods of the EMA, which means subtracting the short period from the long period of the EMA, in order to identify the trend changes in a time series (Klassen, 2005). This technical indicator depends on the EMA in its calculation, therefore, it possibly gives wrong signals for the share price movements.

From the technical indicators above, the only RSI, introduced in more detail in Section 4.5.1, will be used as input in this research due to, as mentioned earlier, its measurement of the upward to the downward intensities movements of the share prices which, it is believed, helps to improve the share price forecasts. However, this technical indicator is not sufficient on its own to achieve improved financial forecasting models of the share prices from the banking sector. This is because they are not identifying the following:

1. Turning points of the share price movements which identify local points whereby an alteration in the direction of the share prices is observed.
2. Directional intensity in the behaviour of the share prices, which identifies the intensity of the share price movements.

Therefore, the two novel technical indicators salient to financial data were developed in this research so as to improve the share price forecasts of the banking sector. It is expected that these technical indicators will be useful in financial forecasting process in general when used as inputs since they introduce an element of the market knowledge to the modelling application that existing indicators do not provide.

These technical indicators are the Turning Points Indicator variables which addressed the issue in point 1 above, and the Ordinal Market Sentiment Indicator variables which addressed the issue in point 2 above. These novel indicators are introduced below.

3.2.1 Turning Points (TPs)

Turning points are generally defined as the points at which the direction of the time series changes (Farnum and Stanton, 1989; Makridakis *et al.*, 1998). Identifying whether a given point, y_t, is a turning point in a time series depends on the value of the given point in relation to the previous and next $n/2$ value as shown in Equation 3.1.

The turning points technical indicator was developed and used as input in this research when building the forecasting model. It helps identify the turning points of the share price movements and hence help build an improved financial forecasting model by, for example, increasing the number of correctly identified turning points between the actual and the forecast share prices which is regarded by this research as the most influential indicator in financial forecasting (see Section 4.6.1.7).

Two types of turning points technical indicators that can be used in forecasting can be defined. The first uses two values to determine whether a given point is a turning point, with respect to the n nearest values, taking values (0 and 1). Thus, this binary turning points technical indicator, BTP, at time t can be obtained from:

$$BTP_t = \begin{cases} 1 & y_{t-n/2},\ldots\ldots,y_{t-1} < y_t > y_{t+1},\ldots\ldots,y_{t+n/2} \\ 1 & y_{t-n/2},\ldots\ldots,y_{t-1} > y_t < y_{t+1},\ldots\ldots,y_{t+n/2} \\ 0 & otherwise \end{cases} \tag{3.1}$$

where y_t the actual price at time t, n the turning points time window, 1 the point is a turning point, and 0 the point is not turning point.

The second recognises the type of turning point, be it a maxima or a minima. A maxima turning point occurs at time t when the observation at time t is larger than the $n/2$ observations at each side of time t, while the minima turning point occurs at time t when the $n/2$ observations at either side are bigger than the observation at time t.

Thus, the type of turning point technical indicator, TTP, at time t can be obtained from:

$$TTP_t = \begin{cases} +1 & y_{t-n/2},\ldots\ldots,y_{t-1} < y_t > y_{t+1},\ldots\ldots,y_{t+n/2} \\ -1 & y_{t-n/2},\ldots\ldots,y_{t-1} > y_t < y_{t+1},\ldots\ldots,y_{t+n/2} \\ 0 & otherwise \end{cases} \tag{3.2}$$

where y_t the actual price at time t, n the turning points time window, +1 the point is a maxima turning point, -1 the point is a minima turning point, and 0 there is not turning point.

3.2.2 *Ordinal Market Sentiments (OMSs)*

Market sentiments, as introduced in Section 1.2.7, represent an important factor that affects share price movements. Therefore, attempts to measure market sentiments have received much attention in the finance literature (see, for example, Bandopadhyaya and Jones, 2006; Yu and Tam, 2007).

Bandopadhyaya and Jones (2006) measured the Equity Market Sentiment Index (EMSI) using publicly available data. The EMSI was measured by calculating the Spearman Rank Correlation Coefficient[(1)] between the daily returns and the historic volatility of the returns, and multiplying the result by 100 to obtain the result between -100 and 100. More recently, Yu and Tam (2007) developed two indicators to measure investors' attitudes towards risk in the Hong Kong stock market leading to the Risk Appetite Index (RAI) and the Investor Sentiment Indicator (ISI). The RAI compares the expected values of the equity option prices and the historical equity cash prices, while the ISI was based on the current realised return as well as the expected short-term return of the stock market.

Although these measures provide valuable information about the direction of the share price movements (i.e. upwards or downwards), they fail to provide the intensity by which they fluctuate. This intensity provides further and valuable information regarding the forecasting of share price values. In real-life application, the sole knowledge of the direction of the shares constitutes an incomplete piece of information. Therefore, the knowledge of the intensity by which the shares will decrease or increase will provide a superior asset to the financial forecaster.

To this end, the Ordinal Market Sentiments (*OMSs*), a novel measure of the market sentiment was developed in this research as a technical indicator to be potentially

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[(1)] Spearman rank correlation coefficient is a non-parametric measure of correlation used to measure the relationship between two variables when the data is ordered under hierarchical ranks.

used as an input when building the forecasting models. This technical indicator can be calculated based on the daily historic share prices, hence, it can be used as an input to a forecasting model.

Since the range of the data used in building the forecasting models is mostly between -3 and +3 due to normalisation (see Section 4.5.2 for details), the possible values that the *OMSs* can take were restricted to the same range, as shown in Table 3.1 below.

Negative Change			No Change	Positive Change		
Strong	Average	Weak		Weak	Average	Strong
-3	-2	-1	0	+1	+2	+3

Table 3.1: The ordinal market sentiment scale of the share price movements

Empirical works (see, for example, Azoff, 1994; Pyle, 1999; Tarassenko, 1998) have implicitly shown, as a general rule, that input data used in neural network forecasting model are more efficient when they all have the same range. This is because associating the same weight to each input will provide an unbiased feed when building the model.

Using historic data, the *OMSs* at time *t* can be obtained as follows:

1. Perform a linear differencing for the dataset. This was carried out by subtracting the values at time *t* from the values at time *t-1*, i.e. $(y_t - y_{t-1})$. This results in a time series which is the day-to-day change of the share prices.

2. Compute the Inter Quartile Range (IQR) of the differenced time series. The IQR is used as it provides a more reliable range of the linearly differenced time series to limit the possibility of extreme values being present in the data.

3. Divide the IQR by 7 (the number of points in the *OMSs*) to identify the range of class intervals which allow to hierarchically classify the data series values of the linearly differenced time series as *OMSs* values. These values were used as input when building the financial forecasting models.

In this research, as previously mentioned, the *OMSs* were utilized as an input for evaluation in modelling and forecasting the share prices from the banking sector. Furthermore, in the proposed *OMSs* technical indicator, additional components with lower frequency domains (i.e. seasonality) were implemented so as to provide the modelling process with a less erratic movement of the *OMSs* which might help uncover further patterns in the share prices. In practical terms, this modelling was carried out by attributing the coefficient, i.e. slope[(1)], of the regression line with a certain periodicity. Therefore, one value based on weekly, bi-weekly and monthly periodicity was consequently investigated for each dataset and included in the construction of the most suitable forecasting models.

The regression coefficient b was obtained as follows:

$$b_s = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \tag{3.3}$$

where s is the slope periodicity, n is the total number of observations in each period, X in general the independent variables of length s (i.e. 1 to 5 in weekly period, 1 to 10 in two weeks period and 1 to 20 in monthly period), Y in general the share prices in s period, $\bar{X}$ in general the mean of X values in each period, and $\bar{Y}$ in general the mean of Y values in each period.

In practise, the future values of *OMSs* will be provided through expert opinion. However, such expert opinion will not always be accurate. This is because the expert opinion is usually made based on the available financial information in the market, in other words, financial information which is related to the economy, politics, company management, and company performance. More precisely, the company performance, which is represented by the financial statements, is thought to be the most important information used in the establishment of the expert opinion (Firth, 1977; O'Regan, 2006). Conversely, the financial information might not be always truthful (Salafsky and Margoluis, 2003), and this leads the experts to

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(1) In mathematics, the value of the slope is the coefficient b of a regression line $y = bx + a$.

make inaccurate decisions. In addition, a mistake in investment decision-making can also occur. Therefore, an error component was added to the calculated values of the *OMSs* when used as an input during training and testing in order to simulate the uncertainty in the expert opinion. This uncertain component was simulated by adding values generated using the normal distribution to the calculated *OMSs* values.

A normal distribution with mean μ=0 and standard deviation σ=0.1 was initially used, but the standard deviation was iteratively increased by 0.1 until the adequacy of the forecasting models are significantly affected, hence, in order evaluate how accurate the expert need to be.

In genuine out of sample forecasting applications, the TP_t and the OMS_t of the last day of the input data at time t are unknown. This is because calculating the TP_t and the OMS_t values at time t depends on the previous and next value in the time series, as introduced earlier. Therefore, the forecasting process requires these values to be present. To generate these values, when there is no market information available, the following was carried out:

- ***For the TPs***, in order to simulate the expert opinion, the binomial and trinomial distributions, with probabilities based on the percentage of the observed turning points. This way, by assuming the original framework in terms of types of turning points, an unbiased generation of turning points is expected to be produced.

  The binominal distribution was used with the binary turning points while the trinomial distribution was used with the type of turning points technical indicator variables.

  The generated data points, which resemble observation at the last day of the used input data, were added to the available data to forecast the next day's share price.

- ***For the OMSs***, a value of 0 was used to represent as the ordinal market sentiment in the last day of the used data assuming that there is no information available from the market which may affect the share price movement.

Ideally, the models need to employ further market knowledge, including the factors introduced in Section 1.2, as inputs in order to identify **(a)** whether there will be a turning point or not and **(b)** the value of the ordinal market sentiments as introduced in the following section.

3.3 Market Knowledge

Several studies (see for example, Kamruzzaman and Sarker, 2004; Yao and Tan, 2000; Yao *et al.*, 1997) argue that acceptable forecasting models can be built without incorporation of market knowledge into the model. However, the stock prices in the market, as introduces in Section 1.2, are affected by a large number of factors. Therefore, it is expected that using market knowledge (i.e. the factors that affect share prices) as an input when building the forecasting model will lead to improving share price forecasts for the banking sector.

In general, market knowledge can be defined as organised and structured financial information collected by direct observations of the market. The way of collecting the financial information, i.e. the direct observations, is conjectured to be the most commonly used in studying a particular behaviour as it takes place in relation to changes in the stock market.

The market knowledge available at time t, which generally reflects the expert opinion, can be obtained by collecting and studying the daily market information and the factors that affect share prices movements directly or indirectly normally obtained through mainstream media. Hence, at time t, the market knowledge that affects the share price movement at time $t+1$ can be identified as follows:

- ***For the TPs,***

  1. Proceed by speculating where the share price is going to move the next day, time $t+1$, according to the collected market information.

2. Compare the speculated share price movement, obtained from point 1 above, with the actual share prices movement at time t to determine the forecast turning point at time t. For instance, when the actual share price movement at time t was up (↑) and the expected share price movement at time $t+1$ is down (↓), the expected turning point at time t will be (1) as a BTP_t and (+1) as a TTP_t, and so on, as show in Table 3.2 below.

The actual share price movement at time *t* with respect to time *t-1*	The expected share price movement at time *t+1* with respect to time *t*	The expected *TP* at time *t*	
		BTP	***TTP***
↑	↑	0	0
↑	↓	1	+1
↑	⇆	0	0
↓	↑	1	-1
↓	↓	0	0
↓	⇆	0	0
⇆	↑	1	-1
⇆	↓	1	+1
⇆	⇆	0	0

Table 3.2: The determination of the forecast turning point at time *t* in terms of the actual and expected share price movements

where ↑ is a positive change, ↓ is a negative change, and ⇆ there is no change, all with respect to the previous share prices movement.

- ***For the OMSs***, proceed by speculating where the share price is going to move next day, time $t+1$, and the intensity of this movement, according to the collected market information, to determine the value of the *OMSs* at time t, in terms of the *OMSs* scale shown in Table 3.1.

Moreover, in case of using the weekly, bi-weekly or monthly periodicity of the *OMSs* as an input when building the forecasting models, the *OMSs* of the last week, two weeks, or month of the used data can be determined using the same scale of the *OMSs*, introduced earlier, shown in Table 3.1, i.e. the financial expert, in this case, represents the coefficient of each period.

It is worth pointing out that the expert opinion of the weekly, bi-weekly or monthly *OMSs* is usually taken at the beginning of each period.

3.4 Discussion

Two technical indicators which are salient to financial forecasting, namely the Turning points (*TPs*) and the Ordinal Market Sentiments (*OMSs*), were proposed in this research to improve one step-ahead forecasts for the share prices form the banking sector.

In the instance of the *TPs*, this technical indicator was developed to identify the changing points of the direction of the financial time series. Initially, the *TPs* was developed using the values 1 when there is a turning point at time *t* and 0 when there is not, denoted by *BTP*. However, the *BTP* did not take into account the type of turning points (minima and maxima), therefore, further development for this technical indicator was carried out, denoted by *TTP*, to include the value +1 if there is a maxima turning points, -1 if there is a minima turning points and 0 if there is not, at time *t*. It is expected that using the *TTP* helps to improve the share price forecasts in terms of the correctly identified turning points measure between the actual and the forecast share prices. For the *OMSs*, this technical indicator was developed to identify the intensity movement of the time series values in order to improve the share price forecasts in terms of the direction of the shares measure. The *OMSs* takes values from -3 till +3 due to normalisation of the share price time series, used in this research, which usually takes values in this range.

Moreover, a way of measuring the market sentiments that represents the market knowledge was developed to be used as input when forecasting the future share prices. This is because the market knowledge, which represents the factors that affect share prices, is usually the main factor driving the share prices up or down in the market. Therefore, using the market knowledge as input to set up the *TPs* and the *OMSs* in the last day of the used data, as explained in Section 3.3, leads to improving the share price forecasts of the banking sector.

However, when there is no market information available, setting up the *TPs* and the *OMSs* was determined by, for the *TPs*, simulating the turning points using binomial distribution, in case of using the *BTT*, and the trinomial distribution, in case of using the *TTP* while for the *OMSs*, a value of 0 was determined to be used as input at time *t*. These values of the *TPs* and the *OMSs*, which were determined when there is no market information available, do represent an expert opinion and thereafter, possibly lead to producing inaccurate forecasts.

In general, these novel input data will be evaluated for modelling and forecasting the share prices from the banking sector, as presented in Chapter 5.

3.5 Chapter Summary

In this chapter, novel input data, which were developed in this research, were introduced to be used when building the financial forecasting models in order to improve the share price forecasts of the banking sector. The developed input data, which represents a financial expert opinion, were the following:

1. Two technical indicators, namely the turning points and the ordinal market sentiments, used as input when building the forecasting models.
2. Market knowledge used as input when forecasting future share price movements.

It is expected that the two new technical indicators, which addressed the issue in point 1 above, and the market knowledge, which addressed the issue in point 2 above, help to improve the forecasts of the share prices in the banking sector when employed as input in building the forecasting model.

The following chapter introduces the methodology that was employed in this research to forecast the future values of the shares from the banking sector.

CHAPTER 4

RESEARCH METHODOLOGY

4.1 Introduction

This chapter introduces the research methodology that was employed to evaluate the novel input data, introduced in the previous chapter, in building an adequate forecasting model to forecast the future values of shares in the banking sector.

Obtaining an adequate financial forecasting model in this research involves investigating the following:

- The novel forecasting algorithm proposed in this research, introduced in Section 4.7, to model and forecast the financial time series.
- Established and novel input data when building the forecasting model to identify the variables that are salient to financial forecasting.
- The suitability of the established and novel accuracy measures, introduced in Section 4.6.1, in evaluating the performance of the forecasting models to identify a potential measure that can be used to evaluate the forecasting models.
- The use of several forecasting approaches to model the financial time series in order to identify an approach that produces superior models in terms of forecast reliability and interpretation.

The process of data analysis is an indispensable part of any forecasting study (Janacek and Swift, 1995). In this sense, the strategy for this research will rely on analysing the historic share prices and the factors that affect share prices, represent the market knowledge, to produce one step-ahead forecasts for the movement in the future share prices of the chosen banks.

HSBC, Lloyds TSB and the Royal Bank of Scotland (RBS) were chosen as case studies for this research in order to observe their activities and the effect of these activities on their share movements and, hence, forecast their future share prices. The modelling process initially starts with the share prices of HSBC and Lloyds TSB, thereafter, the share prices of the RBS will be used to evaluate the success of the two novel technical indicators, introduced in Section 3.2. Furthermore, in order to investigate the general success of the new developed framework in this research, a model for the share prices of Barclays Bank was obtained and evaluated, as introduced in Section 6.5.

These banks were chosen as they are global banks and their shares are held by a large number of shareholders and are regularly traded. Therefore, they are suitable for this research in that they provide a wealth of potential data.

A summary of each bank used in this research is introduced below.

HSBC Bank Plc. is one of the largest banking and financial services organisations in the world. It provides a wide variety of financial services. Its international network includes over 10,000 offices in 83 countries. HSBC's shares are held by nearly 200,000 shareholders in 100 countries (http://www.hsbc.co.uk).

Lloyds TSB Bank Plc. is the fifth largest bank and one of the most important banking and insurance groups in the UK with operations in 30 countries across the world. It provides a wide range of banking and financial services on domestic and international levels. The shares of this bank are held by a large number of shareholders all over the world (http://www.lloydstsb.com).

Royal Bank of Scotland (RBS) is one of the oldest banks in the UK and considered to be one of the leading banks, with more than 40 branches, in providing the financial and banking services in the world. The shares are held by around 185,000 shareholders (http://www.rbs.co.uk).

Barclays Bank is one of the oldest and largest financial services groups in the UK which operates in over 60 countries with 90 branches. It became, in the 1880s, the first British bank to have its shares listed on the Tokyo and New York stock exchanges (http://www.barclays.co.uk).

4.2 Data Collection

In this research, secondary data in the form of historic daily open share prices of HSBC, Lloyds TSB and RBS, covering the period from 3rd July 2000 until 30th March 2007 was used. In addition, the open share prices of Barclays Bank, covering the period from 1st July 2002 until 12th September 2008 were also investigated. All these share prices were collected from Yahoo Finance's website (http://uk.finance.yahoo.com). The opening share prices usually suffer higher volatility in their movements than other period (Amihud and Mendelson, 1987), however, predicting the opening share prices allows time to trade in the market.

In addition, primary data in the form of the factors that affect share prices were collected, to accumulate market knowledge, to be used as inputs for the forecasting model. This data was collected by direct observations of the market through news and media as it is generally believed to provide an insight on the behaviour, in terms of share values, of the stock market.

In the following section, the research approach of the collected data used in this research is discussed.

4.3 Research Approach

In general, research can be qualitative, quantitative or a combination of both. The present research uses quantitative approaches as these are suitable for its aims and objectives of the research.

The quantitative approaches in forecasting are applied when the patterns contained in past data are assumed to continue into the future (Makridakis *et al.*, 1998). In addition, the most important data used in the empirical analysis of this research is in the form of time series and time series analysis is generally quantitative (Janacek and Swift, 1995).

The modelling and forecasting approaches used in this research are introduced in the next section.

4.4 Modelling Approach

In accordance with the related previous studies introduced in Section 2.4, Artificial Neural Networks (ANN) are considered to be one of the most successful approaches that can be used in modelling and forecasting financial applications in terms of forecast accuracy.

Therefore, the major part of this research concentrated on the application of ANN to forecast the future share prices of the banking sector while the application of other forecasting approaches, in particular the Random Walk and ARCH Models, were employed to provide a benchmark in evaluating the performance of the forecasting models obtained using the ANN.

To follow is a review of the approaches used in this research.

4.4.1 Random Walk Model

The Random Walk (RW) model is widely used for modelling time series, specifically share price time series, as an initial approximation in order to examine whether the share prices follow random movements or not (Chatfield, 1996; Chatfield, 2000; Makridakis *et al.*, 1998). The RW is based on adding a random error to the share price of the previous trading day, at time *t-1*, to predict the future share price, at time *t*. For a time series of share prices, $y_1, \ldots\ldots, y_n$, the RW is given by:

$$y_t(1) = y_{t-1} + z_t \qquad (4.1)$$

where y_{t-1} is the share prices of the previous trading day and z_t is white noise[(1)] which can be generated using a random distribution process such as the normal distribution.

The RW is a naïve model which is generally used when there are no other approaches which can be used to model the time series. It is widely used in the financial forecasting (see, for example, Huang *et al.*, 2006; Maris *et al.*, 2004; McMillan *et al.*, 2000; Wei, 2002; Yu, 2002) as a benchmark model and also to investigate that the time series follows a random movement or not.

4.4.2 ARCH Family of Models

ARCH, stands for AutoRegressive Conditional Heteroskedasticity, is a non-linear forecasting model which was developed in a simplified form by Engle (1982) to become a method that is capable of modelling volatile time series data (Knight and Satchell, 2002; Pena *et al.*, 2001).

In spite of the success of ARCH(q) models in numerous financial applications, as explored by Liew and Chong (2005), the original ARCH algorithm has a number of weaknesses, for example:

- *ARCH tends to overfit the data.* A large lag length q of an autoregressive process and a large number of parameters are usually required when building the forecasting models which leads to the over-prediction of the data values (Aradhyula and Holt, 1988; Bollerslev, 1986; Bollerslev *et. al.*, 1994; Daly, 2008; Knight and Satchell, 2002; Pena *et al.*, 2001).

- *ARCH disregards the evolution, positive or negative, of the time series.* In the modelling, the square of the previous value is utilised to determine the next one. However, in forecasting, the positive and negative traits of these values are essential to obtain an adequate model. This, particularly in financial applications, causes the forecasting to be erroneous and misleading (Pena *et al.*, 2001).

(1) A white noise is a discrete-time process consists of a sequence of random variables which are mutually independent and identically distributed.

To overcome these limitations, Bollerslev (1986) extended the initial ARCH model into the *Generalized* ARCH model of order p and q, which is written as GARCH(p, q). For a time series, $y_1, \ldots\ldots, y_n$, this model can be represented as follows:

$$y_t = c + \varepsilon_t \tag{4.2}$$

where c is the mean of y_t, and ε_t is the random one step-ahead forecast error which is defined as:

$$\varepsilon_t = z_t \sigma_t \tag{4.3}$$

where z_t is a standardized, independent and identically distributed (i.i.d.), random variable with a specific distribution, i.e. $z_t \sim N(0, \sigma_t^2)$, and σ_t is a conditional standard deviation given by the square root of σ_t^2, which is defined as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{4.4}$$

where, σ_t^2 is a function of lag values of ε_t^2 and α_0.

$p \geq 0$ is the order of GARCH process.

$q \geq 0$ is the order of ARCH process. For q=0, the process reduces to the ARCH model.

$\alpha_0 > 0$, $\alpha_i = (0, \ldots\ldots, p)$ and $\beta_i = (0, \ldots\ldots, q)$ are the parameters of the forecasting model. These parameters are assumed to be positive to ensure that the conditional variance σ_t^2 is always positive.

The extension of ARCH model to GARCH model represents an extension of the standard process, AR(R), to a general process, ARMA(R, S) (Akgiray, 1989; Aradhyula and Holt, 1988; Zivot and Wang, 2003), which is given by:

$$\hat{y}_{j,t} = \sum_{r=1}^{R} b_{rj} y_{t-r,j} + \sum_{s=1}^{S} a_{sj} \varepsilon_{t-s,j} \tag{4.5}$$

where ε_t leads the linear regression process, which is defined as:

$$\varepsilon_t = y_t - x_t b \tag{4.6}$$

where y_t is the dependent variable, x_t is the independent variable and b is a set of unknown parameters to be established and investigated.

Given the above, the mean c in Equation (4.2) is now modelled as ARMA(R, S). Hence, ARMA(R, S) with GARCH(p, q) errors model was chosen in this research for modelling and forecasting the share prices of the banking sector. This is because:

- It is considered as an important method in financial forecasting due to its ability to represent the volatility of financial time series (Franses, 1998, Pena *et al.*, 2001; Knight and Satchell, 2002; Zivot and Wang, 2003).
- It is widely used in financial forecasting applications (Franses, 1998; Knight and Satchell, 2002; Gazda and Vyrost, 2003; Mala and Reddy, 2007) and it has been shown to produce acceptable financial forecasting results in numerous previous studies (see, for example, Akgiray, 1989; Husain and Uppal, 1999; Karmakar, 2004; John, 2004).

However, the GARCH Model is limited in using the input data, it is does not allow for using multi data as input when modelling the time series. Therefore, the GARCH Model possibly fails to build acceptable forecasting models, for the time series that suffers high volatility in its movement, in terms of the accuracy measures, direction of the shares, introduced in Section 4.6.1.6, and correctly identified turning points, introduced in Section 4.6.1.7.

Modelling and forecasting financial time series using GARCH models consist of three stages. These are preparation and identification, estimation and testing, and application. Each of these stages is introduced in turn below.

4.4.2.1 Preparation and Identification

This stage involves, in general, the examination of any relevant applications and/or statistical approaches related to the modelling of the financial data under investigating (Chatfield, 1996). Subsequently, this stage identifies suitable parameters, p and q, by usually using the heuristic method, i.e. using experimentation and trial and error techniques.

However, a number of studies (see, for example, Pena *et al.*, 2001; Zivot and Wang, 2003; Shin and Sohn, 2007; Daly, 2008; Zivot, 2008) suggest that lower-ordered GARCH models, such as the standard GARCH(1,1), can be successfully applied in most applications. Therefore, GARCH(1,1) models were investigated in this research as an initial modelling step.

4.4.2.2 Estimation and Testing

This stage measures the efficiency and adequacy of the proposed models in terms of the parameters used when building the forecasting models. In this research, S-PLUS® V. 6 software was used for building forecasting GARCH models.

In general, this stage entails the estimation of parameters leading to the improvement of forecasts. This is realised by means of the accuracy measures used to check whether the estimated parameters provided a good fit to the data when testing the model.

Evaluating the forecasting models can be carried out through the diagnostic checking by analysing the residuals (Franses, 1998; Makridakis *et al.*, 1998; Garcia *et al.*, 2005). This was carried out by plotting the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals in order to check for the adequacy of the constructed GARCH model. Hence, by examining the significant autocorrelations in the residuals, persistent patterns and/or seasonality in the forecasting model can be identified.

In this research, novel statistical metrics (introduced in Section 4.6.1) were developed and used alongside established accuracy measures to measure the performance of the financial forecasting models as additional assertion of the model's adequacy.

As a general rule, if any of the accuracy measures used to evaluate the performance of the forecasting models is unacceptable, then the preparation and identification stage is re-evaluated in order to estimate alternative models. This process is iterated until an adequate forecasting model is obtained.

4.4.2.3 Application

After selecting a concluding forecasting model at the previous stage, one step-ahead forecasts of the future share prices from the banking sector can be produced.

4.4.3 Artificial Neural Networks

The Artificial Neural Networks (ANNs) are non-linear mathematical models which are designed in such a way that they operate in a similar manner to the human brain. ANNs have been applied successfully to numerous fields such as engineering design, medicine, credit evaluation, fraud detection, insurance, and business forecasting (Kaastra and Boyd, 1996; Habra, 2005) and they have been shown to provide superior results compared to other methods as explored in Makridakis *et al.* (1998), Gately (1996), and Hamid (2004).

The justification for implementing the ANNs in this research resides in the superior modelling and forecasting of the share prices they provide. This is because:

- ANNs are suitable for the data used in this research due to their ability to model a non-linear time series.
- ANNs have previously been used to solve complicated problems, especially, in financial forecasting (Azoff, 1994; Gately, 1996; Karunananda, 2002; Tarassenko, 1998; Makridakis *et al.*, 1998; Hamid, 2004; Egeli *et al.*, 2003).
- There is sufficient evidence in the literature to suggest that ANNs frequently succeed in financial forecasting research where other applications fail (see for example, Kamruzzaman and Sarker, 2004; Kaastra and Boyd, 1996; Yao and Poh, 1995; Yao *et al.*, 1997; Yao *et al.*, 1999; Yao and Tan, 2000).

ANN, unlike the GARCH Model, takes a set of input when building the forecasting model, thus, modelling the share prices from the banking sector, which suffer high volatility in their movements, may be more successful.

However, the ANNs depend on the expert's skills and experience in building the financial forecasting models as there is no explicit ANN forecasting model. In addition, the ANNs require a larger number of input data than other forecasting approaches, for example the GARCH model, in modelling time series data (Azoff, 1994; Makridakis *et al.*, 1998; Tarassenko, 1998).

Several types of ANNs have been shown to be suitable in modelling and forecasting time series, such as the Feed-forward Neural Network (Anastasakis and Mort, 2000), Back-propagation Neural Network (BPNN) (Kamruzzaman and Sarker, 2004; Yao and Tan, 2001a; Yao and Poh, 1995), Scaled Conjugate Gradient (SCG) (Kamruzzaman and Sarker, 2004) and Back-propagation with Bayesian Regularization (BBR) (Kamruzzaman and Sarker, 2004; Rech, 2002).

In this research, the BPNN was selected to be used for modelling and forecasting the share prices from the banking sector. This is because it is more efficient than other methods and is a widely used method, particularly in financial applications (Chatfield, 1996; Adya, 1998; Gradojevic and Yang, 2000; Hamid, 2004; Kong and Martin, 1995; Lawrence, 1997; Yao *et al.*, 1997; Yao *et al.*, 2000).

The BPNN is an established neural network forecasting method which usually architecturally consists of three layers which are the input, output and hidden layer. It is worth noting that this last layer is placed between the input and the output layers as it represents the invariant relationships between the inputs and the outputs patterns in neural network models. Each layer consists of one or more interlinked neurons (Azoff, 1994; Chatfield, 1996; Tarassenko, 1998; Pyle, 1999; Dreyfus, 2004).

For example, Figure 4.1 below shows a simple architecture of BPNN with single hidden layer.

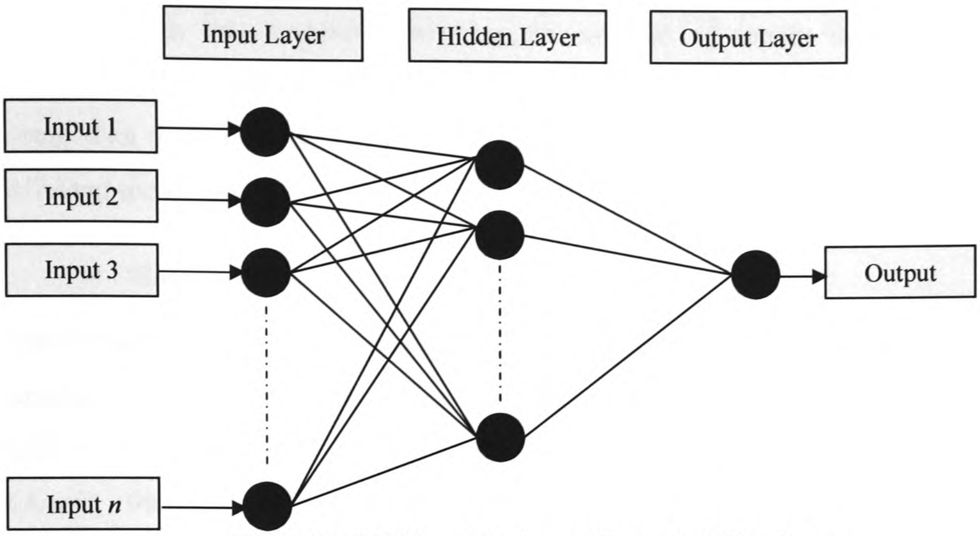

Figure 4.1: BPNN architecture with single hidden layer

The architecture of BPNN, which represents the forecasting model, is introduced below.

4.4.3.1 Back-propagation Neural Network Architecture

The architecture of the BPNN model, as mentioned above, consists of three layers which are the input, hidden and output layers. These are introduced below.

- **Input Layer**

The first layer in neural network architecture is the input layer. Each neuron in this layer represents an input variable which is presented into the network through this layer (Hamid, 2004; Tarassenko, 1998).

Different types of input data which were used in this research include the technical indicators and pre-processed data, these are introduced in Section 4.5. As a rule, including too many input data leads to the possibility of over-fitting the data (Dreyfus, 2004; Tarassenko, 1998). This over-fitting in the forecasting model usually produces a small error on the training set but will produce a larger error when a new dataset is presented to the network and hence unreliable forecasts.

Over-fitting is a superior fit of the model to the training data where the neural network learns the sprier patterns of noise and the random elements in a time series (Clements and Hendry, 1999; Tarassenko, 1998; Makridakis *et al.*, 1998).

Therefore, in this research, reducing the number of inputs was achieved by identifying and removing the inefficient input data from the model, i.e. keeping the input data that affect the output most, and discarding the input data that has least affected the output.

- **Hidden Layer**

Neural network models are usually built using single or multi hidden layers which are used to map the input layer to the output layer (Hamid, 2004). Usually, no more than two hidden layers are used to design the neural network forecasting models (Azoff, 1994; Kaastra and Boyd, 1996; Makridakis *et al.*, 1998). This minimisation of the number of layers relates to the parsimonious framework whereby increasing the number of hidden layers leads to the possibility of over-fitting the data in training process (Kaastra and Boyd, 1996; Tarassenko, 1998) which is explained later on in Section 4.4.3.2.

However, there exists in the research community a consensus that, in the majority of cases, one hidden layer is sufficient to build adequate forecasting models (see, for example, Kaastra and Boyd, 1996; Doumpos and Zopounidis, 2002; Hamid, 2004; Adepoju *et al.*, 2007). Hence, the use of one hidden layer was implemented in this research to design the neural network forecasting models.

Each hidden layer consists of various hidden neurons. There is no standard technique which can be used to determine how many neurons should be employed when designing the neural network. Thus, this is a matter of experimentation that is usually carried out at the model training step (Kaastra and Boyd, 1996; Dreyfus, 2004) which is introduced in details in Section 4.4.3.2. In general, the desired model has as few hidden neurons as is consistent with producing sufficiently good mapping of the input and output data (Kaastra and Boyd, 1996; Tarassenko, 1998; Adepoju *et al.*, 2007). Conversely, the use of too few hidden neurons provides inaccurate mapping of the inputs into outputs (Hamid, 2004). Therefore, to overcome this problem, the construction of the forecasting models in this research started with the number of neurons equalling the total number of input and output data, and thereafter, reducing the number of neurons was achieved. This was carried out by reducing the number of neurons one at a time until an adequate model was obtained.

- **Output Layer**

The final layer in a neural network's architecture is the output layer. The number of neurons in the output layer depends on the application requirements (Azoff, 1994; Hamid, 2004; Habra, 2005). Since the aim of this research is to forecast the open share prices for one step-ahead, one neuron to represent the open share prices was employed in the output layer.

4.4.3.2 Modelling and Forecasting Steps

In general, the process of modelling and forecasting time series using a BPNN is introduced through three steps. These are training the model, testing the model and producing forecasts, as discussed in turn below.

- **Model Training**

Training the model is an initial step of building forecasting neural network models which presents the dataset, including various input data, to the network in order to identify the potential mathematical relationships between the variables in the dataset (Gately, 1996; Pyle, 1999).

The initial stage of this process is to choose the size of the dataset required to train and test the model. It is generally the case that a large proportion of the available dataset is used for training and the remaining smaller proportion is used for testing (Azoff, 1994; Lawrence, 1997; Tarassenko, 1998). In this research, a large proportion of the open share price dataset, approximately 85%, covering the period from 3rd July 2000 until 31st July 2006 was used for training the model. This proportion seems to be sufficient for training since it covers the whole pattern of dataset.

In general, model training is usually performed in two steps (Pyle, 1999). The first step fits the model using different types of input data variables with different model architectures[1] (Lawrence, 1997; Tarassenko, 1998) while the second step verifies the validity of the model by comparing within sample forecasts to the observed values.

In this research, the two steps above (fitting the model and verifying the validity of the model) were investigated, in order to achieve an adequate trained forecasting model, in terms of the accuracy measures introduced later in Section 4.6.1.

The most significant problem in training the neural network is over-training (Lawrence, 1997; Duin, 2000). This is because overtraining leads to the possibility of over-fitting the data. Therefore, care was taken to ensure that network topology and training strategy meant that overtraining did not occur by testing the model (Duin, 2000; Rajanayaka *et al.*, 2003). This was achieved in this research by the following:

1. Stop the training before it starts over-fitting the training data. The point at which training stops depends on the forecasting accuracy measures which do not take into consideration the fitting of the data when evaluating the performance of the forecasting models.

   Hence, an established correctly direction of the shares measure (see Section 4.6.1.6) and the novel correctly identified turning points measure (see Section 4.6.1.7) were considered in this research as an important accuracy measures used to evaluate the performance of the forecasting models.

2. Build a small size of neural network model according to Duin (2000). This is because using a large size network will possibly lead to over-fitting the data. In this study, a small size network was obtained by reducing the number of inputs and the number of neurons in the hidden layer.

   Therefore, reducing the size of the forecasting models was a significant step placed in the forecasting algorithm proposed in this research, as introduced in Section 4.7.

[1] Model architecture refers to the number of input layers, hidden layers and output layers which are used to build the forecasting model.

- **Model Testing**

Testing the model is an assessment of the forecasting capability of the trained forecasting model, achieved in the previous step, using a time window of the time series that was not used in building the model (Azoff, 1994; Tarassenko, 1998; Pyle, 1999). It is conventional that only a small proportion of the data is usually used for testing (Gately, 1996; Lawrence, 1997), which is believed to be sufficient to test the trained model. In this research, the time series, that was not used in model training, covering the period from 1st August 2006 until 30th March 2007, was used for model testing.

Hence, this step entails evaluating the forecast obtained from the trained model to ascertain whether it fits the testing data to an acceptable level or not. If not, that would lead back to the data preparation step to follow the steps to iteratively follow the steps until an adequate testing model is obtained (Pyle, 1999; Lay *et al.*, 1999). In this research, the evaluation of the trained forecasting model, at this step, was carried out in terms of a number of established and novel forecast accuracy measures, as introduced in Section 4.6.1.

- **Producing Forecasts**

After obtaining a concluding forecasting model, it can be employed to produce a forecast of future values of the time series. In this study, producing the forecast of the future values of the share prices for one step-ahead was investigated using the concluding forecasting models.

According to the literature, modelling and forecasting financial time series stop at this point, i.e. after producing a forecast. However, it is expected that the modelling and forecasting should continue with the intention of further improving the forecasts, as proposed in the forecasting algorithm developed in this research, introduced in Section 4.7.

The following section presents the existing input data that are used, in addition to the novel input data introduced in Chapter 3, to model and forecast the share price time series using the BPNN.

4.5 Input Data

The first step of the modelling and forecasting process is to select relevant data to be used as input when building financial forecasting models. The most common data which is pertinent to the banking sector is the historic share prices which were used in this research to build the financial forecasting models. Subsequently, a novel approach to measure relevant market information which drive the share prices up or down, introduced in Section 1.2, was employed as an input as illustrated in Section 3.3, in order to investigate the influences of including this information in the forecasts of the share prices of the case studies.

Two main types of inputs were prepared for building the financial forecasting models, these are technical indicators and data pre-processing technique, as introduced below.

4.5.1 Technical Indicators

In general, technical indicators, introduced in Section 3.2, assemble all the information that is derived by applying some mathematical transformations to the data in a time series in order to understand the general movement of the time series. The technical indicators are usually used to depict a time series, those with high volatility in their movements, by reducing the influence of noise, outliers and other sources of variation.

Among many different technical indicators, as introduced in Section 3.2, the financial technical indicator Relative Strength Index (RSI) was one of the input data used in this research, in addition to the two novel technical indicators this research has developed, when building the forecasting models.

It is expected that the RSI helps to build improved forecasting models due to its measurement of the upward intensity to the downward intensity of the share prices.

RSI at time t takes values between 0 and 100. It is obtained from:

$$RSI_t = 100 - \left(\frac{100}{1 + RS_t} \right) \quad (4.7)$$

where RS_t is the relative strength and obtained from:

$$RS_t = \frac{\frac{1}{n} \sum_{j=1}^{n} Positive\ Differencing_j}{\frac{1}{n} \sum_{j=1}^{n} Negative\ Differencing_j} \quad (4.8)$$

where,

n	window size of relative strength index
Positive Differencing	positive changing of daily share prices
Negative Differencing	negative changing of daily share prices

The value of RSI is defined as 0 when there are no upward changes and 100 when there are no downward changes in the share prices in period n.

In this research, the RSI for weekly, bi-weekly, tri-weekly and monthly periods were used.

4.5.2 Data Pre-processing

After collecting the data and before employing it as input to build the forecasting model, the data usually undergo several pre-processing techniques. Data pre-processing is generally used to depict a time series, those with high volatility in their movements, by reducing noise, outliers, and other sources of variation and hence to increase the quality of the data since the success of any forecasting model depends on the quality of the input data (Getely, 1996; Pyle, 1999; Bao, 2000; Manousakis, 2000).

In general, data pre-processing is an integral part of neural network applications (Tarassenko, 1998; Manousakis, 2000) and it is necessary to obtain effective results.

The data pre-processing techniques used in this research include:

➢ Linear Differencing

Linear differencing measures the difference between the values in a time series separated by a specific time period. It is often used to remove the trend and seasonality in linear time series data (Chatfield, 1996).

First-order linear differencing is obtained by subtracting the value at time *t-1* from the following value at time *t* (Makridakis *et al.*, 1998).

It is obtained from:

$$\nabla y_t = y_t - y_{t-1} \tag{4.9}$$

Seasonal differencing is calculated by subtracting the corresponding preceding value at time *t-s* from the value at time *t*, where *s* is the periodicity of the seasonal component of the data.

It is obtained as:

$$\nabla_s y_t = y_t - y_{t-s} \tag{4.10}$$

where ∇y_t is a non-seasonal differencing and $\nabla_s y_t$ is a seasonal differencing.

Some studies refer to the differenced dataset as the "momentum" (see for example Getely, 1996; Yao and Poh (1995)).

➢ Normalization

Normalization is a pre-processing technique obtained by using the standard deviation and the mean of the time series. It is used to standardize the absolute range of the values of a time series (Azoff, 1994; Tarassenko, 1998; Pyle, 1999). This is particularly useful in share prices because of the high volatilities in the stock market.

Normalizing the input data variables, i.e. converting all the input data to the same scale, is very important in building ANN forecasting models since the ANN can be trained better using a similar scale of input data (Azoff, 1994; Tarassenko, 1998;

Pyle, 1999). This is because using input data with a similar scale leads to associating the same weight to each input and hence providing an unbiased feed when building the model.

For a given value y_t, its normalized value can be obtained from:

$$z_t = \frac{y_t - \bar{y}}{SD}, \qquad (4.11)$$

where z_t now has mean equals 0 and SD equals 1,

y_t the actual prices at time *t*,

$\bar{y}$ the mean of the dataset and defined as:

$$\bar{y} = \frac{1}{n}\sum_{t=1}^{n} y_t \quad , \qquad (4.12)$$

SD the standard deviation of the dataset and defined as:

$$SD = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(y_t - \bar{y}\right)^2} \qquad (4.13)$$

➢ **Data Smoothing**

Smoothing the data, which leads to reducing the noise and random components of the time series, is useful in understanding the underlying trend of the data. It also helps to remove the erratic frequencies from the dataset (Gately, 1996).

Many methods to smooth the time series data exist. In this study, the Moving Average (MA) was used. This is an established technique to smoothing time series data (Gately, 1996; Jarrett, 1987; Pyle, 1999).

Different window sizes can be used to calculate the moving average of the time series which lead to series with different smoothing levels. As a general rule, bigger window sizes produce smoother series.

There are two types of moving average that can be used in forecasting (Makridakis *et al.*, 1998; Johnston *et al.*, 2003), these are: Centred Moving Average (CMA), and Prior Moving Average (PMA).

The calculation used in the CMA is dependent on the number of values in the time window through which the moving average is calculated and whether the number of observations in the window is odd or even (Makridakis *et al.*, 1998).

The CMA for an odd number of observations is obtained from

$$CMA_t = \frac{1}{n}\sum_{j=-((n-1)/2)}^{((n-1)/2)} y_{t+j}\ , \tag{4.14}$$

while the CMA for an even number of observations is obtained from

$$CMA_t = \frac{1}{2(n-1)}\left(\sum_{j=-(n/2)}^{(n/2)-1} y_{t+j} + \sum_{j=-(n/2)+1}^{(n/2)} y_{t+j}\right) \tag{4.15}$$

where n is the moving average time window.

The PMA, which is positioned next to the last number of the time window, is obtained from.

$$PMA_t = \frac{1}{n}\sum_{t-n+1}^{t} y_t \tag{4.16}$$

In general, the PMA is used to smooth time series data for the forecasting applications. This is because it depends only on the past observations while, by contrast, calculating the CMA depends on past and future observations.

The thinking is that the window size of the moving average indicates the period of which the moving average is a summary. For example, the moving average for one working week is denoted by ($5MA_t$), while the moving average for two working weeks is denoted by ($10MA_t$). Using different window sizes to calculate the moving average leads to series with different smoothing levels. It is expected that these input help to improve the performance of the forecasting models due to their providing a clear underlying trend of the time series.

In the next section, modelling and forecasting tools which include the accuracy measures, which are used to evaluate the performance of the forecasting models, and the model identification tools, which are used to explore the time series components whether it is a trend, seasonal or cyclic component.

4.6 Modelling and Forecasting Tools

This section introduces the modelling and forecasting tools that are used for building the financial forecasting model. These tools include the accuracy measures and model identification tools as follows.

4.6.1 Accuracy Measures

Accuracy measures are necessary to evaluate the performance of the forecasting models by measuring the suitability of the model to decide if it is producing reliable forecasts or not (Makridakis *et al.*, 1998; Pena *et al.*, 2001). Accuracy measures can also be used to compare two or more forecasting models (Farnum and Stanton, 1989).

Accuracy measures are usually calculated by running formulae that measure the scaled difference between the actual values and forecast values (e.g. the difference between actual and forecast values) (Pena *et al.*, 2001). If the results of the accuracy measures are unacceptable then normally the model must be rebuilt.

Established accuracy measures that are used to evaluate the performance of the forecasting models are introduced next.

4.6.1.1 Mean Error (ME)

The Mean Error is the average of the forecast error (e_t) between the actual values and forecast values. It is calculated by taking the summation of the forecast error divided by the number of forecasts (Makridakis *et al.*, 1998; Bowerman and O'Connell, 1987).

It is obtained from:

$$ME = \frac{1}{n}\sum_{t=1}^{n} e_t \qquad (4.17)$$

where n is a number of forecast errors, e_t is a forecast error at time t and is computed by taking the difference between the actual value and forecast value (Makridakis *et al.*, 1998).

It is defined as:

$$e_t = y_t - y_t(k) \tag{4.18}$$

where $y_t(k)$ is k step-ahead forecast made at time t and k is a steps-ahead.

This measure is trivial as it does not provide a useful indication of the forecasting accuracy. This is because if there are positive and negative errors, this measure will offset one against another and give a misleading result near to zero (Makridakis *et al.*, 1998; Bowerman and O'Connell, 1987).

This problem is often solved by taking either the absolute or the square of the forecast errors (e_t) to remove the signs of the forecast errors (Bowerman and O'Connell, 1987; Syntetos and Boylan, 2005; Makridakis *et al.*, 1998).

4.6.1.2 Mean Absolute Error (MAE)

The Mean Absolute Error is computed by taking the average of the absolute forecast errors (Makridakis *et al.*, 1998). The absolute is used to rid the forecast errors of their signs.

The MAE is obtained from:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t| \tag{4.19}$$

The advantage of using the MAE is that it is measured by the scale (and units) of the original time series and thus is easier to understand and communicate (Makridakis *et al.*, 1998; Farnum and Stanton, 1989). Conversely, since it depends on the scale of the time series when measuring the forecasting accuracy, it is not useful to be used in making a comparison between the forecasting models of different time series or different periods of time (Makridakis *et al.*, 1998).

4.6.1.3 Mean Square Error (MSE)

The Mean Square Error is computed by taking the average of the squared forecast errors (Makridakis *et al.*, 1998). The square is used here to make the entire forecast errors positive.

The MSE is obtained from:

$$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \tag{4.20}$$

For the purpose of comparing the result of MSE with the result of another measure, the square root of the MSE is usually taken in order to obtain a metric that is on the scale of the original series (Farnum and Stanton, 1989). This resulting measure is called the *Root Mean Square Error (RMSE)*, calculated as:

$$RMSE = \sqrt{MSE} \tag{4.21}$$

This measure, similarly to the MAE, depends on the scale of the time series when measuring the forecasting accuracy. Hence, it is not useful to be used in making a comparison between the forecasting models obtained from different time series or different periods of time (Makridakis *et al.*, 1998). Therefore, using the percentage error, as shown below, will be useful to solve this problem.

4.6.1.4 Mean Percentage Error (MPE)

The Mean Percentage Error is the average of all of the percentage errors (PE_t) in a time series. It is calculated by taking the summation of the percentage error divided by the number of forecasts (Makridakis *et al.*, 1998).

It is obtained from:

$$MPE = \frac{1}{n}\sum_{t=1}^{n} PE_t \tag{4.22}$$

where PE_t is a percentage error of the time period t and is computed as the percentage of the difference between the actual value and forecast value to the actual value (Makridakis *et al.*, 1998).

The PE_t is defined as:

$$PE_t = \left(\frac{y_t - y_t(k)}{y_t} \right) * 100 \qquad (4.23)$$

The MPE suffers the same limitations as with the ME, therefore, it is a trivial measure. Hence, the Mean Absolute Percentage Error is normally used to evaluate forecasting models (Makridakis *et al.*, 1998).

4.6.1.5 Mean Absolute Percentage Error (MAPE)

The Mean Absolute Percentage Error is the average of all of the absolute percentage errors in a time series. It is calculated by dividing the sum of the absolute percentage errors by the number of forecasts (Makridakis *et al.*, 1998).

It is obtained from:

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} |PE_t| \qquad (4.24)$$

The MAPE is a percentage and thus does not depend on the scale of the time series as it transforms the error (e_t) to percentage of the error (PE_t) to the actual value and averages the percentage in period *n*. Therefore, it can be used to make comparisons between numerous forecasting models built using different time series or different periods of time.

In this research, two main existing accuracy measures were used to measure the reliability of the forecasting models. These were the conventional RMSE and MAPE. The RMSE is a widely used measure in the forecasting applications in spite of the limitation of this measure especially when there is an extreme value in the dataset, however, this problem was limited in this research by normalising the data. The MAPE was used due to its ability to make comparisons between different forecasting models. One limitation of the MAPE when an observation value equals zero, however, this problem was limited in this research as there is no share price equals zero.

Due to the nature of this research, the forecast errors which are represented by the established RMSE and MAPE are not on their own sufficient to evaluate the performance of the forecasting model. This is because these forecast errors do not take into consideration the direction of the shares, which might be considered to be more important than how the forecasts fit the data in the financial forecasting.

Therefore, the accuracy measure which evaluates the performance of the forecasting models based on the direction of variability in the share prices is needed. Of these, the established direction of the shares was used and a novel truth table to evaluate the performance of the models in correctly identifying turning points in share prices was developed, as introduced next.

4.6.1.6 Correctly Identified Direction of the Shares (DoS)

Correctly identified direction of the shares, or "Correctness Gradient", was introduced by Yao and Poh (1995). It represents the correctness of the directional change by making a comparison between the changes of the actual values and the changes between the actual and forecast values.

This measure helps to learn about the trend of the shares by evaluating the direction of the forecast prices comparing to the direction of the actual prices.

It is obtained as:

$$DoS = \frac{\sum_{t=1}^{n} g_t}{n} \qquad (4.25)$$

where,

$$g_t = \begin{cases} 1 & (y_t(1) - y_t) = 0 \\ 1 & (y_{t+1} - y_t) * (y_t(1) - y_t) > 0 \\ 0 & otherwise \end{cases} \qquad (4.26)$$

4.6.1.7 Correctly Identified Turning Points

A turning point (*TP*), as introduced in Section 3.2.1, is a point in which the direction of the time series changes. It can be determined for the actual and forecast values using Equation 3.1.

It is expected that using the turning points as an accuracy measure to evaluate the financial forecasting models, helps to improve the selection of the adequate financial forecasting models. Using the turning points as a metric in forecast evaluation is vital to investors so that they obtain an enhanced understanding of the market's underlying dynamics and fluctuations and can relate to the model's performance in their day-to-day dealing. This measure is important to the investors which it helps to identify when the direction of the shares will be changed in the future.

Therefore, two complementary measures of the correctly identified turning points were used to evaluate the performance of forecasting models. These measures are the Sensitivity and the Specificity of Prediction of Turning Points. Sensitivity refers to the percentage of correctly identified positive values (positive in sense used when talking about type I and II errors) to the total number of positive values (i.e. true positive), while the specificity refers to the percentage of correctly identified negative values to the total number of negative values (i.e. true negative), as shown in Table 4.1 below.

		Actual Turning Points	
		1	**0**
Forecast Turning Points	**1**	***True Positive***	*False Positive*
	0	*False Negative*	***True Negative***

Table 4.1: The sensitivity and specificity of correctly identified turning points

where,

True Positive	when	I actual *TP* equals 1 forecast *TP*
False Positive	when	1 actual *TP* equals 0 forecast *TP*
True Negative	when	0 actual *TP* equals 0 forecast *TP*

False Negative when 0 actual *TP* equals 1 forecast *TP*

Hence, sensitivity and specificity are obtained from:

$$\text{Sensitivity of Predicted Turning Points} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{4.27}$$

$$\text{Specificity of Predicted Turning Points} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}} \tag{4.28}$$

However, this set of accuracy measure disregards the type of turning points, whether turning points are maxima, minima or 'not turning points', as introduced in Section 3.2.1. Therefore, the accuracy measure presented above was further developed in this research to take into account the maxima (denoted by *+1*), minima (denoted by *-1*) turning points and 'not turning points' (denoted by *0*). These values are determined using Equation 3.2. Table 4.2 gives the truth table including the type of turning points.

For each type of turning points (i.e., maxima, minima or 'not turning point'), the sensitivity refers to the percentage of correctly identified points to the total number of points, while the specificity refers to the percentage of the correctly identified points of the two other types over the total number of points of these types.

		Actual Turning Points		
		+1	**-1**	**0**
Forecast Turning Points	**+1**	*A*	*B*	*C*
	-1	*D*	*E*	*F*
	0	*G*	*H*	*I*

Table 4.2: The novel table of the sensitivity and specificity of correctly identified type of turning points

where,

A	true maxima positive	i.e.	+1 actual *TP* equals +1 forecast *TP*
E	true minima positive	i.e.	-1 actual *TP* equals -1 forecast *TP*
I	true negative	i.e.	0 actual *TP* equals 0 forecast *TP*
B	false maxima positive	i.e.	+1 actual *TP* equals -1 forecast *TP*
C	false maxima positive	i.e.	+1 actual *TP* equals 0 forecast *TP*
D	false minima positive	i.e.	-1 actual *TP* equals +1 forecast *TP*
F	false minima positive	i.e.	-1 actual *TP* equals 0 forecast *TP*
G	false negative	i.e.	0 actual *TP* equals +1 forecast *TP*
H	false negative	i.e.	0 actual *TP* equals -1 forecast *TP*

Therefore, the maxima, minima and 'not turning points' sensitivity and specificity measures can be obtained using:

$$\textit{Sensitivity of Predicted Maxima Turning Points (NX)} = \frac{A}{A+D+G} \tag{4.29}$$

$$\textit{Specificity of Predicted Maxima Turning Points (PX)} = \frac{E+I}{B+C+E+F+H+I} \tag{4.30}$$

The sensitivity and specificity of predicted minima turning points are obtained using

$$\textit{Sensitivity of Predicted Minima Turning Points (NN)} = \frac{E}{B+E+H} \tag{4.31}$$

$$\textit{Specificity of Predicted Minima Turning Points (PN)} = \frac{A+I}{A+C+D+F+G+I} \tag{4.32}$$

The sensitivity and specificity of predicted 'not turning points' are obtained using

$$\textit{Sensitivity of Predicted 'Not Turning Points' (NP)} = \frac{I}{C+F+I} \tag{4.33}$$

$$\textit{Specificity of Predicted 'Not Turning Points' (PP)} = \frac{A+E}{A+B+D+E+G+H} \tag{4.34}$$

It is worth noting that the maximum value, of the measures above, that can be obtained is 100%, and the minimum value is 0%. In general, assuming all other conditions equal higher percentages of the sensitivity and specificity of predicted turning points, for all types, imply a superior forecasting model.

4.6.2 Model Identification Tools

Model identification tools are used to explore whether the time series present a trend, seasonal and/or cyclic component. The two main tools used in this exploratory exercise are the AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF), while other tools, such as time plots and lag plots, are also available to the modeller. The ACF and PACF play an important role in the exploratory data analysis of time series.

4.6.2.1 Autocorrelation Function (ACF)

The ACF provides information about the correlation of the observations with themselves at lag k in time series (Makridakis *et al.*, 1998; Farnum and Stanton, 1989).

The autocorrelation function, r_k, at lag k is computed as:

either

$$r_k = \frac{\sum_{t=1}^{n-k}\left(y_t - \bar{y}\right)\left(y_{t+k} - \bar{y}\right)}{\sum_{t=1}^{n}\left(y_t - \bar{y}\right)^2}, \tag{4.35}$$

or

$$r_k = \frac{Cov\left(y_t, y_{t+k}\right)}{var\left(y_t\right)} \tag{4.36}$$

where n is a number of observations in time series, $\bar{y}$ is the average of observations in time series, Cov is a covariance function depends only on the lag k and var is a variance of y_t.

4.6.2.2 Partial Autocorrelation function (PACF)

The PACF is a conditional coefficient which provides information about the correlation between the observation y_t and the previous observation at lag k, y_{t-k}, in the time series after removing the possible effects of the relationship between the observations at previous time lags (Makridakis *et al.*, 1998; Farnum and Stanton, 1989).

The partial autocorrelation function, r_{kk}, at lag k is computed as:

$$r_{kk} = \frac{r_k - \sum_{j=1}^{k-1}\left(r_{k-1,j}\right)\left(r_{k-1}\right)}{1 - \sum_{j=1}^{k-1}\left(r_{k-1,j}\right)\left(r_j\right)} \tag{4.37}$$

where r_k is the autocorrelation function at lag k and r_j is the autocorrelation function at lag j, where $j=1,2,3,\ldots\ldots,k-1$.

In general, the forecasting process has to follow a procedure or technique that can be used in modelling and forecasting the financial time series.

As there is no standard algorithm that can be used in modelling and forecasting the financial time series. One aim of this research is the development of a generalized forecasting algorithm that can be applied in modelling and forecasting the share prices of the banking sector, as introduced in the following section.

4.7 The Novel Forecasting Algorithm

This section introduces a novel generalised algorithm that can be used for modelling and forecasting the share prices from the banking sector in order to facilitate the building of an improved financial forecasting model.

Two notable works attempting to address this issue were proposed in Kaastra and Boyd (1996) and Yao and Tan (2001b), as introduced in Section 2.2.5. However, in spite of the success of these proposed algorithms to achieve adequate forecasting models, the application of the proposed algorithms cannot be generalised because of the following limitations:

1. The algorithms offer no feed-back and feed-forward mechanisms to update the input data used to build the forecasting model when an inadequate forecasting model is obtained.

2. The algorithms offer no feed-back mechanism to update the prior information when an unacceptable forecast value is obtained comparing to the expected value in terms of the market information.

3. The algorithms offer no accumulative learning mechanism to update the prior information in the end of each forecasting process. The objective of this mechanism is to further improve the financial forecasting models in terms of, for example, the forecast accuracy, as there is no perfect model can be built.

The feed-back and feed-forward mechanisms refer to in these limitations are believed to improve the modelling of time series as they allow for rectifications and updates to the performance of the constructed models. These are anticipated to better represent the process neural network forecasters adopt and hence yield improved models in terms of learning about the problem at hand and forecast accuracy.

Therefore, to avoid the limitations above, a novel forecasting algorithm, given in Figure 4.2, is proposed in this research. It can be seen from Figure 4.2 that the algorithm proposes feed-back and feed-forward mechanisms that, when followed, may lead to obtaining superior forecasting models.

Furthermore, from a practical point of view, prior information regarding contemporary forecasting tools and/or techniques is necessary in order to maximise the success of the modelling by the forecaster. Moreover, during the modelling, unnecessary additional inputs may intervene in the process hence the need to reduce the amount of parameters of the obtained models so to, primarily, avoid over-fitting and, thereby, generalise the forecasting models.

As can be seen in Figure 4.2, six steps are proposed for the novel algorithm. These steps are **1)** Data Selection, **2)** Data Preparation, **3)** Models Training, **4)** Refining the Models, **5)** Models Testing, and **6)** Making Forecasts, with feed-back and feed-forward mechanisms at steps 3,4,5 and 6.

The proposed modelling and forecasting steps are introduced next.

4.7.1 Data Selection

The first step of the modelling and forecasting process is identifying, from the available data, a set of potentially useful data variables to be used in building the forecasting model. All relevant or possibly relevant data should be investigated at this step for possible inclusion.

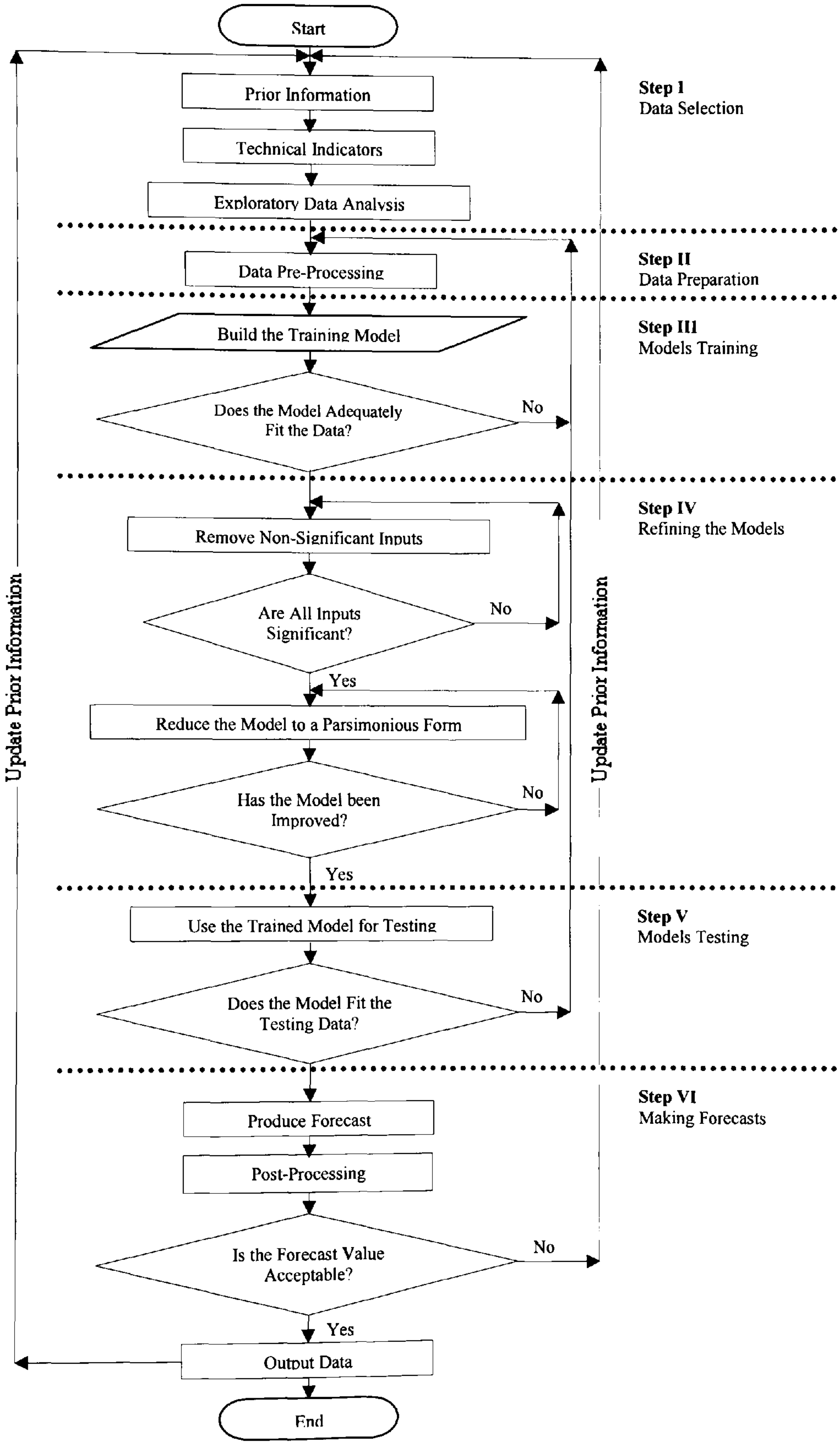

Figure 4.2: Developed Forecasting Model Building Algorithm

The most common data which is pertinent to the present subject matter and relates directly to the case studies are:

1. The historic share prices.
2. The financial market information, which represents a financial expert's opinion.

In this research, the historic open share prices were used, which fall within point 1 above, while other types of data, which fall within point 2 above, were used as input, as introduced in Section 3.3, in order to improve the forecasts of the share prices from the banking sector.

It is proposed that this step consists of three main stages, as follows:

4.7.1.1 Prior Information

Prior information refers to all the relevant information available to the analyst at the beginning of the forecasting process. In addition to the related data which is mentioned above, prior information may include:

- Available forecasting approaches that can be used to forecast the share prices,
- Available experience and knowledge, and
- Available infrastructure such as software and facilities.

Which of these is to be used in modelling can be determined by using evidence from the literature and the analysts' own experience.

4.7.1.2 Technical Indicators

This step investigates the existing and proposed technical indicators that can be obtained using the available information.

As mentioned in Sections 3.2 and 4.5.1, the utilisation of technical indicators was carried out in this research in such a way that they were designed in the proposed algorithm.

4.7.1.3 Exploratory Data Analysis

Exploratory data analysis (EDA) is an important step in time series analysis. It provides an exploration of the data before starting with the forecasting process. The first step of EDA is usually the plotting of the time series to obtain an overview of the dataset. This step is useful to identify anomalies such as missing data and outliers.

In this research, a number of missing observations were identified through this step were found and subsequently replaced by taking the average of the previous and the next share prices, taking into consideration the seasonality s of the data, i.e. y_{t-s} and y_{t+s}. This is so that the missing value is estimated from:

$$\hat{Y}_t = \frac{y_{t-s} + y_{t+s}}{2}, \tag{4.38}$$

where $\hat{Y}_t$ is the estimated value, y_{t-s} is the previous share price in periodicity $s=5$ and y_{t+s} is the next share price in periodicity s.

Whilst the values of the public holidays [1] were equated in this research to the close share prices of the previous trading day, so that.

$$\hat{Y}_{t,holiday} = y_{t-1,\,previous\,close\,price} \tag{3.39}$$

Other EDA techniques involve plotting the autocorrelation function (ACF) and partial autocorrelation function (PACF), introduced in Section 4.6.2, to identify if the time series was seasonal and the periodicity of that seasonality.

4.7.2 Data Preparation

In this step, the data is usually subjected to pre-processing operations in order to increase its quality since the success of any forecasting model depends on the quality of the input data.

[1] Public holidays include Christmas day, Easter day and bank holidays.

As introduced in Section 4.5.2, the utilisation of pre-processing techniques was conducted in this research so that they were designed in the proposed algorithm.

4.7.3 Models Training

Model training, as introduced in Section 4.4.3.2, is the initial step in building forecasting models. This is carried out by selecting the size of the dataset to be used to train the model and determining the architecture of the model.

In general, when a forecasting model obtained at this step gives unacceptable results, this leads to a revisiting of the Data Preparation step in order to learn from the first experience, choose a different set of inputs and possibly a different model or a different modelling approach. This is to be iterated until improved results are obtained.

Model training, in case of using a neural network, can be carried out using different types of input data employing different model architectures (Lawrence, 1997; Tarassenko, 1998), while in GARCH Model involves finding appropriate initial estimates of the parameters, using the ACF and the PACF, and then successively refining them until the optimum values of the parameters are obtained.

However, in case of using neural networks, the most significant problem in this step, as mentioned in Section 4.4.3.2, is over-training (Makridakis *et al.*, 1998; Tarassenko, 1998). To avoid this problem, a decision has to be made as to when the training should stop. The point at which the training stops usually depends on the established benchmarks of the forecasting accuracy measures used in empirical works, such as, the correctly identified direction of the shares, introduced in Section 4.6.1.6, and the sensitivity and specificity of predicted turning points, introduced in Section 4.6.1.7.

4.7.4 *Refining the Models*

4.7.4.1 Remove Non-Significant Inputs

This step involves keeping the inputs that significantly explain the output and discarding the inputs that have little or no effect on explaining the output.

In this research, this was carried out by removing the input data one at a time and evaluating the performance of the model at each step. In the instance of the GARCH model, this step is carried out by removing the non-significant parameters.

4.7.4.2 Reduce the Model to a Parsimonious Form

This is an optimization that minimizes the number of parameters and accuracy measures simultaneously, so that the model would have an optimum accuracy measure with as few parameters as possible.

4.7.5 *Models Testing*

As introduced in Section 4.4.3.2, model testing is used to investigate the capability of the trained mode in share price forecasts using a time window that the model has not been trained on.

Generally, when the testing step gives unacceptable results in terms of the used accuracy measures, this would lead to reversing the data preparation step to use a different set of inputs and possibly build a different model or use a different model approach. This is usually iterated until acceptable results are obtained.

4.7.6 *Making Forecasts*

After obtaining an adequate forecasting model, a forecast of the future values of the shares can be produced.

In many cases, a post-processing step is applied to the forecasts in order to revert them back to the data's original scale. This is why it is essential that all pre-processing methods applied to the output variable are reversible.

After making the forecasts, the forecast values can be checked by the financial experts to ascertain whether they are reliable in terms of the expected future movement produced. If not, the forecasting model building steps are started again from the beginning with updated prior information. This process is iterated until acceptable forecasts are obtained.

However, as there is no guarantee that the adequate forecasting model built is suitable for the future, therefore, updating the prior information is proposed in this algorithm to possibly develop the forecasting model for financial application.

4.8 Chapter Summary

The research methodology to explore, analyse and forecast the share prices from the banking sector was presented in this chapter. It included a review of each of the forecasting methods which were used for modelling the financial forecasting models and producing forecasts of the future share prices. These methods were the RW Model, the GARCH Model and the BPNN.

The RW is a naïve model since it is used when there is no appropriate approach for modelling the time series. The BPNN performs better than the GARCH Model since it allows employing a set of inputs when building the forecasting models in comparison to the GARCH Model which does not allow the use of more than one input.

This chapter discussed the existing input data that were examined to build adequate financial forecasting models. It also illustrated the accuracy measures that were used to evaluate the performance of the forecasting models which include a developed accuracy measure namely the correctly identified turning points measure, shown in Section 4.6.1.7. This accuracy measure is expected to improve the selection of an adequate financial forecasting model since it helps to identify when the direction of the shares will be changed in the future, this will be useful to the investors.

Finally, a novel financial forecasting algorithm, introduced in Section 4.7, for modelling and forecasting the share prices from the banking sector was introduced. This algorithm overcomes the limitation in the previous forecasting algorithms by including the feed-back and feed-forward mechanisms which, it is believed, help to improve the modelling of financial time series and, hence, provide adequate forecasting models. Furthermore, in the novel algorithm, the practicality of forecasting is included (i.e. prior information and reduction to parsimonious form) which may respectively provide a further insight on the feasibility and generalisation of the investigated models.

In addition, modelling and forecasting financial time series, according to the literature, usually stop after producing a forecast. However, it is expected that the modelling and forecasting should continue with the intention of further improving the forecasts as there is no guarantee that the adequate forecasting model built is suitable for the future. Therefore, a proposed step was included to the forecasting algorithm, introduced in Section 4.7, to carry on modelling the time series.

CHAPTER 5

MODELLING SHARE PRICES

5.1 Introduction

The historic daily open share prices of the banking sector, in particular the shares of HSBC, Lloyds TSB and Royal Bank of Scotland (RBS) as case studies, were analysed to produce one step-ahead forecast value of their share values. One step-ahead forecasts were used since the likelihood of the daily events which affect today's share price, positively or negatively, continuing to the next trading day is normally high. Therefore, these models are expected to be of real practical benefit.

The algorithm proposed in this research (introduced in Section 4.7) was used to build forecasting models for the share prices of the case studies from the banking sector. The main tables and figures detailing this analysis are located at the end of this chapter, whilst some recapitulative tables are provided between the texts.

The historic daily open share prices of the case study shares, covering the period from 3rd July 2000 until 30th March 2007, suffer high volatility in their daily movements, as shown in Figures 5.1, 5.2, and 5.3 for HSBC, Lloyds TSB and RBS respectively. These data are listed in Appendix C.

The initial stage of modelling and forecasting the share prices was plotting the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the data, as introduced in Section 4.6.2, to identify Univariate patterns such as whether the time series used in this research were seasonal and, if so, the periodicity of that seasonality. The ACF and PACF for HSBC, Lloyds TSB and

Royal Bank of Scotland are shown in Figures 5.4, 5.5 and 5.6 respectively. It can be seen from these figures show a weekly seasonality for HSBC, a bi-weekly seasonality for Lloyds TSB and a monthly seasonality is detected for RBS.

A number of missing observations in the investigated time series, which represent the share prices of the public holidays, were identified through the EDA step, as introduced in Section 4.7.1.3. These missing observations, comprising less than 0.01% for each dataset, were estimated by taking the average of the two valid nearest neighbours, i.e. the existing previous and next share prices for $s = 1$ as shown in Equation 4.38. It is expected that, in the evaluation of the missing values, this estimation procedure is particularly suitable to financial forecasting due to the high volatility the datasets exhibit. Thus, the share prices at time t can be more accurately calculated based on the share prices at time $t-1$ and $t+1$, rather than using the share prices of the previous and following seasonal-lagged trading days.

In general, the selection of an initial list of potentially useful forecasting models in this research was carried out by determining the models which yielded acceptable forecast accuracy measures. Hence, choosing a concluding forecasting model, in this research, depended on both the sensitivity and specificity of predicting the type of turning points in the data, as introduced in Section 4.6.1.7. In addition, the direction of the shares, as introduced in Section 4.6.1.6, was also used, giving a total of seven accuracy measures to consider in the model selection process. These seven accuracy measures, in addition to the conventional RMSE and MAPE, were taken into account in this research as they are believed to best demonstrate the forecast accuracy of each forecasting model. These accuracy measures also reflect important aspects of the decision making process employed in the financial forecasting.

Within the accuracy measures mentioned above, benchmark values were used to comparatively evaluate the forecasting models obtained in this research. These benchmark values were obtained from established forecasting models published in the literature and forecasting models built using Random Walk (RW) and GARCH models. The following section introduces these benchmark models.

5.2 Benchmarking

The benchmark models considered in this research were constructed using the RW and the GARCH approaches, employed on the entire datasets with which this research is concerned. The results obtained from these forecasting models were utilised as benchmarks to evaluate the results obtained using the BPNN. In addition, the results obtained from a key application of financial forecasting introduced in (Gately, 1996) were used as benchmark values. These are introduced in the next section. A standard financial benchmark is the buy, sell or hold advice which is usually given by the financial experts. Although this is an important benchmark, it part of the financial evaluation which is recommended as future work based on this research.

5.2.1 Established Benchmark Values

The established benchmark model, which was presented by Gately (1996), was selected to be used as a benchmark model in this research. This model, further detailed in Appendix B, generated accuracy measures using Gately's own data, which were employed in this research, as given in Table 5.1.

MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
	Maxima (XN)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
0.30%	31%	31%	48%	42%	43%	30%	49%

Table 5.1: The accuracy measures of the established benchmark model

This table shows that the benchmark model generated a vey low MAPE value while the other accuracy measures (the sensitivity of predicted turning points, the specificity of predicted turning points and the direction of the shares) yielded accuracy measures inferior to 50%. Hence, this benchmark model produced unreliable turning point forecasts the vast majority of the time. Therefore, these accuracy measures are deemed unsatisfactory since, in this research, a threshold of 50% was aimed for as it was believed to be the minimum acceptable value.

5.2.2 Random Walk Models

A random walk model for the data, as introduced in Section 4.4.1, can be obtained by adding a random error to the share price of the previous trading day to predict the future share price as stated in Equation 4.1. Hence, random errors, for each time series, were generated using the normal distribution based on mean *0* and standard deviation equals to the standard deviation of the first-order linearly differenced time series. The calculation of the standard deviation using first-order linear differencing was sufficient to avoid the influence of trend and any outliers and/or outlying time windows in the datasets.

The accuracy measures of the RW models for HSBC, Lloyds TSB and RBS based on one step-ahead forecasts are given in Table 5.2.

Banks	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
		Maxima (XN)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
HSBC	1.34%	25%	23%	37%	36%	37%	18%	49%
Lloyds TSB	2.18%	21%	21%	39%	37%	37%	16%	49%
RBS	2.11%	23%	22%	37%	35%	35%	18%	47%

Table 5.2: The accuracy measures of the forecasting models obtained using the Random Walk model

The interpretation of these accuracy measures is given in Section 6.2.1.

5.2.3 GARCH Models

The determination of the concluding Univariate GARCH model was carried out in this research by choosing the model with acceptable significance level of the parameters at 5% level of significance and by evaluating the ACF and PACF of the residuals for any remaining patterns.

Similarly to the RW, in order to avoid the persistence of outliers and/or outlying time windows and hence achieve stationary data which is a condition to build a forecasting GARCH model (Engle, 1982; Bollerslev, 1986), the first-order seasonal and non-seasonal linear differences of the data were carried out, if necessary, and the resulting series were modelled using GARCH. In the experimental modelling of the datasets, using the seasonality shown in Section 5.1 for each bank, seasonal differencing was used on all three datasets. All models failed to yield significant parameters. Thus, non-seasonal differencing was applied to the case study datasets which resulted in unsatisfactory results being obtained in the exception of HSBC.

A conclusive model was obtained for HSBC, this model based on a GARCH(1,1) ARMA(2,2) model and was fitted using the SPLUS-GARCH function. The model in terms the ACF and PACF of the residuals is displayed in Figure 5.7.

Following the GARCH model identification guide lines, the suggested model for the HSBC dataset was found for the dataset as follows,

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + b_1 \sigma_{t-1}^2 + \varepsilon_t \qquad (5.1)$$

where

$$\varepsilon_t = y_t - \left(\phi_1 y_{t-1} + \phi_2 y_{t-2} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2}\right) \qquad (5.2)$$

$$with \begin{cases} a_0 = 0.03841 \\ a_1 = 0.95893 \\ \phi_1 = -0.35177 \\ \phi_2 = -0.99403 \\ \theta_1 = 0.35961 \\ \theta_2 = 0.99401 \end{cases}$$

The accuracy measures from the one step-ahead forecasts obtained from this model are given in Table 5.3.

Banks	**MAPE**	**Sensitivity of Predicted Turning Points**			**Specificity of Predicted Turning Points**			**Direction of Shares (DoS)**
		Maxima (XN)	**Minima (NN)**	**Not TPs (NP)**	**Maxima (PX)**	**Minima (PN)**	**Not TPs (PP)**	
HSBC	0.86%	1%	2%	48%	35%	35%	2%	51%

Table 5.3: The accuracy measures of the forecasting models for HSBC Bank obtained using the GARCH model

The concluding forecasting model for HSBC Bank, displayed in Figure 5.8, shows a one-day lag along the time axis. Therefore, this model is unsatisfactory in terms of the forecasting.

The following section introduces modelling the share prices of the banking sector using the BPNN.

5.3 Neural Network Modelling

The historic daily share prices were normalized and pre-processed prior to their inclusion as inputs to the forecasting models.

Given that seasonality has been indicated in the datasets used in this research, seasonal components were taken into consideration in the data preparation step. Hence, input data used includes the historic open share prices for every single detail one week before and weekly linearly differenced data. The inputs used in ANN modelling of the case study data at time *t* to obtain forecasts y_{t-1} were:

1) The historic share prices on the day, y_t, one day before, y_{t-1}, two days before, y_{t-2}, three days before, y_{t-3}, four days before, y_{t-4}, and five days before, y_{t-5}.

2) First-order and weekly linearly differences of the time series (∇y_t and $\nabla_s y_t$).

3) Smoothed data using crude moving average with different time windows. In this research, time windows of one working week ($5MA_t$), two working weeks ($10MA_t$) one working month ($20MA_t$), two working months ($40MA_t$) and three working months ($60MA_t$) were used to smooth the share price time series of the case studies and, hence, used as inputs when building the forecasting models.

In addition to the pre-processed data, technical indicators were investigated as inputs in building the forecasting models. The technical indicators considered were:

4) The Relative Strength Index (RSI) for weekly, bi-weekly, tri-weekly and monthly periods.

5) The novel technical indicators developed in this research. These are the daily Turning Points (*TPs*) which include the Binary Turning Points (*BTPs*) and the Type of Turning Points (*TTPs*), and the Ordinal Market Sentiments (*OMSs*). These technical indicators measure market knowledge and include it as input to the forecasting models.

It is worth noting that the pre-processed data and the technical indicator (*RSI*) were selected to be considered as inputs to the forecasting models due to their demonstrated success in modelling and forecasting the financial time series in key established studies, as introduced in Section 2.2.

The historic daily open share prices of HSBC, Lloyds TSB, and Royal Bank of Scotland covering the period from 3rd July 2000 until 31st July 2006 were used to train the forecasting models.

Modelling the dataset of HSBC and Lloyds TSB, especially in training step, was investigated, firstly, without and, then, with the market knowledge as input. In the next step, the modelling of the RBS was carried out to evaluate the input data, which successfully improved the accuracy of the forecasting models, used to model the HSBC and Lloyds TSB datasets, in particular, the *TTPs* and the *OMSs*.

5.3.1 Modelling without Market Knowledge

In the first instance, the Univariate forecasting models of HSBC and Lloyds TSB were trained without using the market knowledge as input. That is, the models were built without using the developed technical indicators, which represent the market knowledge, as inputs. These technical indicators, as presented in Section 3.2, include the Turning Points (*TPs*) and the Ordinal market Sentiments (*OMSs*) technical indicator variables.

At the training step of the BPNN modelling on the investigated datasets, only a small portion of all the potential forecasting models to be obtained (i.e. a total of

50 models for each dataset) were retained for further modelling. Hence, 40% of the 50 models, i.e. 20 models for each dataset, were selected as they yielded optimum conventional forecast accuracy measures (RMSE and MAPE) and the smallest number of inputs. Furthermore, these 20 forecasting models were believed to be a representative sample of the performance of the first step of the back-propagation modelling technique.

These forecasting models, shown in Tables 5.4 and 5.5 for HSBC and Lloyds TSB respectively, were generally unsatisfactory in terms of all the accuracy measures employed in this research, especially, the very low percentages observed for the NX, NN and PP. By brief visual inspection of Table 5.4, the most adequate model at this step for HSBC with a total number of 10 inputs yielded forecast accuracy measures of 2%, 3% and 2% for the NX, NN and PP respectively. Similarly, for Lloyds TSB, the value of 0% was obtained for the same accuracy measures with a total number of 10 inputs.

Given that the modelling above of HSBC and Lloyds TSB share prices has not achieved acceptable forecasting models, additional modelling steps were conducted on the 40% sample of forecasting models presented above for HSBC and Lloyds TSB. Thus, in the next section, technical indicators, constituting the market knowledge, were included in the modelling of the datasets.

5.3.2 Modelling with Market Knowledge

In this section, the developed technical indicators, *TPs* and *OMSs*, were individually added as inputs and thereafter combined in view of evaluating the resulting forecasting models compared to models built without using the market knowledge as input. The steps carried out are introduced below.

5.3.2.1 Binary Turning Points (*BTPs*)

The *BTPs* was added as an input in the modelling of each time series. This input, as shown in Tables 5.6 and 5.7 for HSBC and Lloyds TSB respectively, improved the forecasting models, compared to the model introduced in Section 5.3.1, in terms of the accuracy measures considered in this research. The concluding model at this step for HSBC, as highlighted in Table 5.6, has 13 inputs and yielded forecast accuracy measures of 8.86, 0.72%, 41%, 30%, 56%, 48%, 51%, 36% and 82% for the RMSE, MAPE, NX, NN, NP, PX, PN, PP and DoS respectively.

Similarly, given in Table 5.7, the concluding model at this stage for Lloyds TSB produced accuracies of 9.23, 1.10%, 56%, 35%, 52%, 48%, 55% 42% and 80% for the RMSE, MAPE, NX, NN, NP, PX, PN, PP and DoS respectively, with a total number of 11 inputs.

In the following section, the *BTPs* was replaced by the Type of Turning Points (*TTPs*). This novel measure, as introduced in Section 3.2.1, provides better insights into the correctly identified turning points (maxima and minima), hence allowing a further understanding of the underlying dynamics in the time series.

5.3.2.2 Type of Turning Points (*TTPs*)

The results obtained by including *TTPs* as input are given in Tables 5.8 and 5.9 for HSBC and Lloyds TSB respectively. It can be seen from these tables that the inclusion of the type of turning points technical indicator, *TTPs*, as an input further improved the performance of the forecasting models. The concluding forecasting model obtained at this step for HSBC, built with 13 inputs, yielded forecast accuracy measures of 8.55, 0.70%, 57%, 57%, 47%, 54%, 54%, 46%, and 89% for the RMSE, MAPE, NX, NN, NP, PX, PN, PP and DoS respectively. For Lloyds TSB, as highlighted in Table 5.9, the concluding model had 11 inputs and yielded accuracy measures of 9.52, 1.12%, 57%, 63%, 47%, 57%, 55%, 46% and 80%.

In the instance of HSBC, the accuracy measures NX, NN, PX, PN, PP and DoS were increased when the *TTPs* were introduced to the model, with an overall average improvement of 10%. Furthermore, in the instance of Lloyds TSB, the NN and the PX improved from 35% to 63% and from 48% to 57% respectively.

Therefore, encouraging the implementation of the *TTPs* was shown to improve the forecasts in terms of all the accuracy measures with the exception of a little decrease in the NP.

In the next section, the Ordinal Market Sentiments, *OMSs*, is employed on its own as input. The *OMSs*, by informing on the intensity of the share price movements, provides a further and more extensive understanding of the time series, as opposed to the application of the *TTPs* alone.

5.3.2.3 Ordinal Market Sentiments (*OMSs*)

The forecasting models shown in Tables 5.4 and 5.5 for HSBC and Lloyds TSB respectively were all retrained after adding the *OMSs* as an input to them. The results, introduced in Tables 5.10 and 5.11 for HSBC and Lloyds TSB respectively, show that including this input increases the quality of the forecasting model. More specifically, as highlighted in Table 5.10, the most adequate model at this step for HSBC showed forecasts accuracy of 5.97, 0.50%, 50%, 49%, 59%, 57%, 57%, 46% and 71% for the RMSE, MAPE, NX, NN, NP, PX, PN, PP and DoS respectively. In the same way, as highlighted in Table 5.11, the most adequate model for Lloyds TBS presented forecasts accuracy of 6.14, 0.75%, 50%, 56%, 59%, 61%, 59%, 47% and 70%.

By inspection of the forecasts errors for both the HSBC and Lloyds TSB, improved forecast compared to the application of the *TTPs* alone were obtained in terms of the RMSE, MAPE, the rate of NP, PX and PN.

In conclusion, the inclusion of the novel technical indicators proposed in this research as inputs in forecasting models for the case studies was shown to improve the performance of the forecasting models. More specifically, the forecasting models include the *TTPs* and the *OMSs* were found to be of particular interest as they provide valuable insight on the predicted intensity of the direction of the shares and the presence of turning points. Therefore, the next step was to combine these two technical indicators (the *TTPs* and the *OMSs*) as inputs when building the forecasting models. The next section thus examines this new implementation.

5.3.2.4 Type of Turning Points (*TTPs*) and Ordinal Market Sentiments (*OMSs*)

In this section, the *TTPs* and *OMSs* were used together as inputs when building the forecasting models for HSBC and Lloyds TSB respectively. Results indicate that including these inputs further improved the forecasting models compared to the forecasting models built using the *TTPs* and *OMSs* separately, in terms of all nine accuracy measures used in this research. For instance, the most adequate forecasting model at this step for HSBC, as highlighted in Table 5.12, yielded forecast accuracy values of 6.21, 0.52%, 80%, 76%, 62%, 72%, 73%, 64% and 79%, with 14 inputs. Similarly, as highlighted in Table 5.13, the forecast accuracy values of the most adequate forecasting model for Lloyds TSB were 4.54, 0.50%, 75%, 77%, 66%, 73%, 72%, 64% and 82%, in the respective order of the RMSE, MAPE, NX, NN, NP, PX, PN, PP and DoS.

Therefore, by comparison with the models constructed using the *TTPs* and *OMSs* separately, the effect of including these technical indicators together as inputs to the ANN model alongside the other inputs produced a superior forecasting model of the case study datasets in spite of a slight decrease in the DoS, in particular, for HSBC models.

5.3.2.5 Discussion

Figures 5.9 and 5.10 give the one step-ahead RMSE and MAPE of HSBC and Lloyds TSB obtained from the 20 models of each case study built thus far in this research. It can be seen from these figures that, in general, the MAPE of the forecasting models using the combination of the *TTPs* and *OMSs* was superior compared to the ones using the *BTPs*, the *TTPs* and the *OMSs* alone. In terms of the RMSE, the forecasting models using the *OMSs* and the models using the combination of the *TTPs* and *OMSs* were comparable.

Similarly, Figures 5.11 and 5.12 give the NX, NN, NP, PX, PN, PP and DoS of the 20 models of the four modelling steps for HSBC and Lloyds TSB. Whilst in terms of the NX, NN, NP, PX, PN and PP, the combination of the *TTPs* and *OMSs* yielded superior models compared to when the *BTPs*, the *TTPs* and the *OMSs* add were used alone, the DoS of the forecasts from models incorporating the *TTPs* on its own were comparable.

In conclusion, although acceptable results are obtained, in a general manner, amongst the implementation of technical indicators as inputs when building the forecasting models for the share prices from the banking sector, the combination of the novel *TTPs* and *OMSs* provided superior one step-ahead forecasts of the case studies investigated.

The following section introduces further examination of the effectiveness of the new technical indicators, *TTPs* and *OMSs*, as inputs in modelling the historic open share prices of the Royal Bank of Scotland (RBS).

5.3.3 Modelling RBS: An Additional Case Study

The modelling steps and the experiments introduced in Section 5.3.2 provided strong evidence to conclude that using the novel *TTPs* and *OMSs* technical indicators as inputs improves the performance of the forecasting models. Therefore, similarly to the forecasting models constructed for HSBC and Lloyds TSB, the times series of the RBS was modelled. The adequate forecasting model at this step, as highlighted in Table 5.14, was selected, with forecast accuracy of 12.77, 0.53%, 77%, 76%, 60%, 70%, 70%, 63% and 83%, in the respective order of the RMSE, MAPE, NX, NN, NP, PX, PN, PP and DoS.

Therefore, adequate models for the three time series investigated in this research with superior forecasts were obtained. Following these encouraging results, further refinements to the models obtained in this research were investigated. To this end, from a practical point of view, minimising the cost of the production of forecasts which is necessary to the efficiency of a company and simulating the uncertainty in the expert's opinion about the state of the market were investigated in this research as introduced in next section.

5.3.4 Further Modelling and Development

This section introduces further modelling and development of the share prices of the banking sector by **1)** examining lower frequency domains of the *OMSs* in modelling the share prices and **2)** adding an uncertainty element to the calculated values of the *OMSs*.

5.3.4.1 Lower Frequency Domains of the *OMSs*

The adequate forecasting models for the share prices of HSBC, Lloyds TSB and RBS, as introduced in Section 5.3.2.4 and 3.3.3, included the daily *OMSs* technical indicator as an input. Therefore, in a practical sense, the expert opinion would be required on a daily basis to produce the one step-ahead forecast for the share prices of the banking sector. However, the cost/effectiveness relation would be high due to the high frequency by which the expert opinion will be required. Attending to minimize this cost, the daily *OMSs* was replaced with one that is measured on weekly, bi-weekly and monthly bases, which were calculated using the slope, as presented in Section 3.2.2.

However, as shown in Tables 5.15, 5.16 and 5.17 for HSBC, Lloyds TSB and RBS respectively, using the weekly, bi-weekly and monthly *OMSs* as inputs when building the forecasting models achieved inferior forecasting models in terms of all accuracy measures employed in this research compare to model built using the daily *OMSs*. In terms of the models' forecast accuracy values, using the weekly, bi-weekly and monthly *OMSs* led to an increase in the RMSE and the MAPE, as shown in Figure 5.13. Moreover, a notable reduction in the values of NX, NN, NP, PX, PN, PP and DoS was observed, as shown in Figure 5.14, for the three banks.

Therefore, in this research, lower frequencies of the *OMSs* were insignificant inputs in building conclusive financial forecasting models for the share prices of the banking sector. Therefore, the daily *OMSs* were adopted in this research.

5.3.4.2 Simulating Uncertainly in Financial Advice

As introduced in Section 3.2.2, errors in investment decision-making may occur. Therefore, an element of uncertainly was added to the calculated values of the *OMSs* when used as an input in building the forecasting models. This element, as introduced in Section 3.2.2, was calculated using the normal distribution with mean μ=0 and standard deviation σ=0.1, 0.2, 0.3 and so on.

However, it can be shown that the normal distribution with mean μ=0 and standard deviation σ=0.1 does not change the directional intensity of the *OMSs*, this means that the expert's opinion will always be accurate, while the normal distribution with mean μ=0 and standard deviation σ=0.2, 0.3, 0.4 and 0.5 changes the directional intensity of the *OMSs* by 2%, 9%, 20% and 30% respectively. Therefore, a random variable generated from a normal distribution with mean μ=0 and standard deviation σ=0.2 was added to the original *OMSs*, as an initial stage, when building the forecasting models. This was carried out by adding the error variables to the original daily *OMSs* to simulate the errors in the expert opinion.

The forecast accuracy of the forecasting models obtained using *OMSs* included an error are listed in Tables 5.18, 5.19 and 5.20 for HSBC, Lloyds TSB and RBS respectively. These tables show an increase in the RMSE and the MAPE and a slight decrease in the NX, NN, NP, PX, PN and PP with comparable DoS, compared to forecasting models built using the original *OMSs*.

However, the forecasting models of each bank built using the *OMSs* included a percentage error of 30% (determined by adding a normal distribution with mean μ=0 and standard deviation σ=0.5 to the original *OMSs*) produced acceptable accuracy measures compared to the concluding forecasting models built using the *TTPs* and the original *OMSs* separately and generally comparable with the concluding models built using both the *TTPs* and the daily *OMSs* together, as shown in Figures 5.15 and 5.16.

As a result, the forecast models built using the *OMSs* that including a percentage error of 30%, shown in Tables 5.18, 5.19 and 5.20 for HSBC, Lloyds TSB and RBS respectively, were adopted. Hence, to use these models, the expert opinion used in these models can be no more than 70% correct for the model to produce adequate forecasts. This percentage is believed to best reflect the veracity of daily forecasting in the banking sector.

5.3.5 Refining the Models

In order to avoid the over-fitting of the data and to generalise the forecasting models it is necessary to reduce the size of the neural network forecasting model selected in the previous step. This was carried out by refining the forecasting model, as introduced in the novel algorithm presented in Section 4.7, by removing the non-significant inputs and reducing the forecasting model to a parsimonious form.

5.3.5.1 Removing Non-Significant Inputs

Removing the non-significant inputs, as introduced in the proposed algorithm in Section 4.7.4.1, allows for the reduction of the size of the neural network forecasting framework. For the models obtained so far this was carried out by removing an input at a time and evaluating the performance of the forecasting model. Tables 5.21, 5.22 and 5.23 give the accuracy measures of the models built in this step for HSBC, Lloyds TSB and RBS respectively.

Table 5.21, for HSBC, shows that the forecasting model number 1 is superior to the concluding forecasting model obtained in the previous step, highlighted in the same table. This model obtained by removing the historic open share prices for four days before (y_{t-4}), was improved in terms of the RMSE, NX, PN, PP and DoS, which were 6.92, 69%, 67%, 59% and 79% for the concluding model obtained in the previous step and 6.86, 71%, 68%, 60 and 80% for the concluding refined model at this step. Hence, the y_{t-4} is a non-significant input for modelling HSBC time series.

Table 5.22 for Lloyds TSB shows that the moving average for three months, (60MA) was a non-significant input to the forecasting model, as shown in the forecasting model number 9. This model generated accuracy measures comparable with the adequate forecasting models obtained in the previous step (highlighted in the table) which were 7.00, 0.85%, 64%, 66%, 59%, 66%, 65%, 54% and 76% for the concluding model obtained in the previous step, and 7.08, 0.87%, 65%, 68%, 59%, 66%, 65%, 54% and 75% for the concluding refined model at this step, for the RMSE, the MAPE, NX, NN, NP, PX, PN, PP and DoS respectively.

For RBS, the refinement step, as shown in Table 5.23, for the conclusive model obtained in the previous step show that both the historic open share prices four days before (y_{t-4}) and the *RSI* technical indicator for one week were non-significant inputs. However, this refined forecasting model, the forecasting model number 10 in Table 5.23, produced forecast accuracy measures comparable with the adequate model obtained in the previous step after removing the historic open share prices four days before, y_{t-4}, and the *RSI* technical indicator for one week. These forecast errors, in terms of all accuracy measures employed in this research, were 16.14, 0.71%, 73%, 69%, 57%, 65%, 66%, 59% and 81% for the concluding model obtained in the previous step, while for the concluding refined model at this step, the forecast errors were 16.59, 0.72%, 73%, 69%, 58%, 66%, 66%, 60% and 80%, for the RMSE, the MAPE, NX, NN, NP, PX, PN, PP and DoS respectively.

A part of refining the forecasting models is reducing the forecasting model to a parsimonious form, as introduced in the proposed algorithm in Section 4.7.4.2. This is introduced in turn below.

5.3.5.2 Reducing the Model to a Parsimonious Form

This step involved reducing the size of the neural network by reducing the number of neurones in the hidden layer of the forecasting model, as introduced in the proposed algorithm (Section 4.7).

It can be seen in Table 5.24 that for HSBC, the forecasting model with 10 neurons in the hidden layer was selected as a concluding forecasting model. This model was selected in terms of the NX, NN, NP, PX, PN, PP and DoS which were comparable with the concluding model obtained in the previous step, highlighted in the same table, in spite of a slight increase in the RMSE and the MAPE.

For Lloyds TSB, Table 5.25 shows that the forecasting model with 12 neurons in the hidden layer was superior to the concluding model obtained in the previous step, which was built using 13 neurons in one hidden layer, in terms of all accuracy measures employed in this research. Hence, this model was selected as a concluding forecasting model to forecast the future share prices of Lloyds TSB.

For RBS, the forecasting model with 10 neurons in the hidden layer, as shown in Table 5.26, generated lower RMSE and MAPE than the concluding model obtained in the previous step and achieved comparable NX, NN, NP, PX, PN, PP and DoS with the concluding model obtained in the previous step. Therefore, this model was selected as a concluding forecasting model to forecast the future share prices of the RBS.

In conclusion, one model for each time series was identified as a concluding forecasting model. The concluding forecasting model for HSBC consisted of 13 inputs (y_{t-3}, y_{t-2}, y_{t-1}, y_t, 5MA, 10MA, 20MA, 40MA, ∇y_t, $\nabla_5 y_t$, *RSI*, *TTPs* and *OMSs* with an uncertainly element of 30%) with 10 neurons in one hidden layer. For Lloyds TSB, the concluding forecasting model consisted of 12 inputs (y_{t-4}, y_{t-3}, y_{t-2}, y_{t-1}, y_t, 5MA, 10MA, 20MA, 40MA, ∇y_t, *TTPs* and *OMSs* with an uncertainly element of 30%) with 12 neurons in one hidden layer. The concluding forecasting model for RBS consisted of 11 inputs (y_{t-3}, y_{t-2}, y_{t-1}, y_t, 5MA, 10MA, 20MA, 40MA, ∇y_t, *TTPs* and *OMSs* with an uncertainly element of 30%) with 10 neurons in one hidden layer.

Figures 5.17, 5.18 and 2.19 give the within sample one step-ahead forecasts for HSBC, Lloyds TSB and RBS obtained using the models above. It can be seen from these figures that the data was generally well-fitted by the models with no evidence of systematic errors in these forecasts.

The following section introduces the testing step of the concluding model achieved above for each bank.

5.3.6 Models Testing

The next step in the proposed algorithm (see section 4.7) is model testing. Testing the concluding trained model was the final step carried out before using the models to produce forecasts for the share prices of the case study datasets. This step is necessary to investigate the capability of these models in share price forecasts using a different time window.

Therefore, testing the concluding models of HSBC, Lloyds TSB and RBS was performed using the period from 1st August 2006 until 30th March 2007. The results, given in Table 5.27, show that testing the concluding model of each bank produced comparable accuracy measures with the ones obtained from the training and refining steps. These accuracy measures were, for HSBC, 74%, 70%, 47%, 61%, 63%, 50% and 74%, for Lloyds TSB, the accuracy measures were 56%, 62%, 54%, 60%, 60%, 47% and 68%, and for RBS, they were 57%, 56%, 58%, 59%, 56% and 60%, for the NX, NN, NP, PX, PN, PP and DoS, respectively.

5.4 Chapter Summary

The modelling of the share prices of three banks was employed and evaluated in this chapter and was carried out using three forecasting approaches, which were the RW Model, GARCH Model and BPNN.

In the beginning, the modelling of the share prices of the case studies was conducted using the Random Walk and the GARCH approaches. In addition to an established application in financial forecasting, the results of the RW and GARCH approaches were also used as benchmarks to evaluate the performance of forecasting models constructed under the BPNN approach.

In general, modelling the share prices of case studies yielded superior results whilst following the modelling steps proposed in the novel forecasting algorithm developed in this research.

In addition, modelling the share prices of the banking sector, using the BPNN, shows that using the developed technical indicators, *TTPs* and *OMSs*, as inputs yielded superior forecasting models of the share prices of the case studies. Furthermore, it can be noted that the concluding models obtained included a set of inputs which were y_{t-3}, y_{t-2}, y_{t-1}, y_t, 5MA, 10MA, 20MA, 40MA, ∇y_t, *TTPs* and *OMSs*.

After testing the forecasting models, one step-ahead forecast for the share prices of each bank was investigated using the concluding forecasting models. This is introduced in the following chapter.

HSBC Models	No. of Input Data	Input Data																	No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
		t-5	t-4	t-3	t-2	t-1	t	5MA	10MA	20MA	40MA	60MA	1^{st} order differencing	Weekly order differencing	RSI one week	RSI two weeks	RSI three weeks	RSI one month				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
1	11	×	×	×	×	×	×	×	×	×	×	×							12	11.84	1.07 %	1%	2%	49%	35%	35%	1%	49%
2	12	×	×	×	×	×	×	×	×	×	×	×	×						13	11.92	1.04 %	3%	3%	44%	33%	33%	3%	50%
3	12	×	×	×	×	×	×	×	×	×	×	×		×					13	11.74	1.02 %	2%	3%	45%	34%	33%	2%	51%
4	13	×	×	×	×	×	×	×	×	×	×	×	×	×					14	11.63	1.01 %	2%	3%	45%	34%	33%	2%	51%
5	13	×	×	×	×	×	×	×	×	×	×	×	×		×				14	11.34	0.98 %	3%	5%	45%	35%	34%	3%	51%
6	13	×	×	×	×	×	×	×	×	×	×	×	×			×			14	11.39	0.99 %	4%	4%	44%	34%	34%	4%	52%
7	13	×	×	×	×	×	×	×	×	×	×	×	×				×		14	11.48	0.99 %	2%	4%	45%	34%	33%	3%	52%
8	13	×	×	×	×	×	×	×	×	×	×	×	×					×	14	11.27	0.97 %	2%	4%	45%	34%	33%	2%	51%
9	16	×	×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	17	11.84	1.04 %	4%	4%	45%	34%	34%	3%	50%
10	14	×	×	×	×	×	×	×	×	×	×	×	×	×	×				15	10.64	0.93 %	3%	4%	46%	34%	34%	3%	48%
11	13	×	×	×	×	×	×	×	×	×	×		×	×	×				14	11.08	0.96 %	3%	5%	46%	35%	34%	3%	49%
12	13		×	×	×	×	×	×	×	×	×	×	×	×	×				14	11.42	1.00 %	4%	5%	45%	34%	34%	4%	50%
13	10		×	×	×	×	×	×	×	×	×		×						11	10.94	0.93 %	2%	3%	45%	33%	33%	2%	49%
14	11		×	×	×	×	×	×	×	×	×		×		×				12	13.61	1.03 %	1%	4%	46%	34%	33%	2%	49%
15	12		×	×	×	×	×	×	×	×	×		×	×	×				13	11.75	1.03 %	5%	4%	46%	34%	34%	4%	50%
16	11	×	×	×	×	×	×	×	×	×	×		×						12	11.20	0.98 %	3%	3%	45%	34%	33%	3%	50%
17	12	×	×	×	×	×	×	×	×	×	×		×	×					13	11.66	1.01 %	2%	4%	45%	34%	33%	3%	51%
18	11		×	×	×	×	×	×	×	×	×		×	×					12	11.05	0.95 %	2%	4%	46%	34%	33%	3%	49%
19	15		×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	16	11.75	1.05 %	4%	5%	44%	34%	33%	4%	51%
20	11		×	×	×	×	×	×	×	×	×	×	×						12	10.95	0.95 %	2%	2%	44%	33%	33%	2%	49%

Table 5.4: Modelling details and corresponding accuracy measures of the HSBC forecasting models built without market knowledge. Although this table shows that all the forecasting models produced unacceptable accuracy measures, the best model at this step is model 13

Lloyds TSB Models	No. of Input Data	Input Data																	No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
		t-5	t-4	t-3	t-2	t-1	t	5MA	10MA	20MA	40MA	60MA	1st order differencing	Weekly order differencing	RSI one week	RSI two weeks	RSI three weeks	RSI one month				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
1	11		×	×	×	×	×	×	×	×	×	×	×						12	12.25	1.51 %	0%	0%	52%	37%	37%	0%	50%
2	13	×	×	×	×	×	×	×	×	×	×	×	×	×					14	12.81	1.63 %	0%	0%	53%	37%	37%	0%	51%
3	12		×	×	×	×	×	×	×	×	×	×	×	×					13	12.11	1.51 %	1%	0%	50%	36%	36%	0%	50%
4	12	×	×	×	×	×	×	×	×	×	×	×	×						13	12.27	1.56 %	0%	0%	51%	36%	36%	0%	51%
5	12	×	×	×	×	×	×	×	×	×	×	×		×					13	12.89	1.57 %	0%	0%	53%	37%	37%	0%	49%
6	12		×	×	×	×	×	×	×	×	×	×	×		×				13	12.30	1.53 %	0%	0%	52%	37%	37%	0%	51%
7	12		×	×	×	×	×	×	×	×	×	×	×			×			13	12.38	1.57 %	0%	0%	51%	35%	36%	0%	50%
8	12		×	×	×	×	×	×	×	×	×	×	×				×		13	12.55	1.59 %	0%	0%	52%	36%	36%	0%	51%
9	12		×	×	×	×	×	×	×	×	×	×	×					×	13	12.26	1.42 %	0%	0%	50%	36%	37%	0%	49%
10	15		×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	16	13.05	1.60 %	2%	0%	51%	35%	35%	1%	49%
11	10		×	×	×	×	×	×	×	×	×		×						11	12.27	1.52 %	0%	0%	53%	37%	37%	0%	50%
12	11		×	×	×	×	×	×	×	×	×		×	×					12	13.42	1.67 %	0%	0%	52%	36%	37%	0%	49%
13	12		×	×	×	×	×	×	×	×	×		×	×	×				13	14.35	1.73 %	1%	0%	50%	35%	36%	1%	48%
14	13	×	×	×	×	×	×	×	×	×	×	×	×		×				14	12.53	1.49 %	0%	0%	51%	36%	35%	0%	50%
15	14	×	×	×	×	×	×	×	×	×	×	×	×	×	×				15	13.05	1.61 %	0%	0%	54%	35%	36%	0%	51%
16	13	×	×	×	×	×	×	×	×	×	×		×	×	×				14	12.74	1.56 %	1%	0%	52%	36%	35%	0%	49%
17	10		×	×	×	×	×	×	×	×	×	×							11	12.70	1.66 %	0%	0%	54%	37%	37%	0%	48%
18	11		×	×	×	×	×	×	×	×	×	×			×				12	13.44	1.82 %	1%	0%	55%	38%	38%	1%	50%
19	11		×	×	×	×	×	×	×	×	×		×		×				12	12.23	1.54 %	1%	0%	52%	36%	36%	0%	51%
20	13		×	×	×	×	×	×	×	×	×	×	×	×	×				14	12.75	1.57 %	1%	0%	51%	36%	37%	1%	50%

Table 5.5: Modelling details and corresponding accuracy measures of the Lloyds TSB forecasting models built without market knowledge. Although this table shows that all the forecasting models produced unacceptable accuracy measures, the most adequate model at this step is model 11

HSBC Models	No. of Input Data	Input Data: t-5	t-4	t-3	t-2	t-1	t	5MA	10MA	20MA	40MA	60MA	1st order differencing	Weekly order differencing	RSI one week	RSI two weeks	RSI three weeks	RSI one month	BTPs	No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points: Maxima (NX)	Minima (NN)	Not TPs (NP)	Specificity of Predicted Turning Points: Maxima (PX)	Minima (PN)	Not TPs (PP)	Direction of Shares (DoS)
1	12	×	×	×	×	×	×	×	×	×	×	×							×	13	11.12	0.96 %	9%	31%	50%	47%	40%	17%	61%
2	13	×	×	×	×	×	×	×	×	×	×	×	×						×	14	10.37	0.87 %	21%	15%	48%	40%	42%	15%	65%
3	13	×	×	×	×	×	×	×	×	×	×	×		×					×	14	11.41	0.98 %	17%	5%	53%	39%	43%	10%	55%
4	14	×	×	×	×	×	×	×	×	×	×	×	×	×					×	15	9.45	0.80 %	38%	36%	56%	50%	51%	35%	72%
5	14	×	×	×	×	×	×	×	×	×	×	×	×		×				×	15	9.79	0.84 %	36%	31%	57%	49%	51%	33%	72%
6	14	×	×	×	×	×	×	×	×	×	×	×	×			×			×	15	10.06	0.87 %	39%	35%	55%	50%	51%	36%	71%
7	14	×	×	×	×	×	×	×	×	×	×	×	×				×		×	15	10.25	0.87 %	19%	35%	50%	47%	41%	25%	70%
8	14	×	×	×	×	×	×	×	×	×	×	×	×					×	×	15	10.74	0.95 %	31%	41%	54%	51%	47%	34%	65%
9	17	×	×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	×	18	9.79	0.82 %	34%	19%	53%	43%	48%	25%	72%
10	15	×	×	×	×	×	×	×	×	×	×	×	×	×	×				×	16	9.73	0.82 %	39%	42%	56%	52%	51%	39%	77%
11	14	×	×	×	×	×	×	×	×	×	×		×	×	×				×	15	9.86	0.83 %	34%	38%	56%	51%	49%	36%	74%
12	14		×	×	×	×	×	×	×	×	×	×	×	×	×				×	15	9.55	0.82 %	43%	40%	58%	53%	54%	41%	74%
13	11		×	×	×	×	×	×	×	×	×		×						×	12	11.70	1.06 %	34%	40%	56%	51%	49%	36%	58%
14	12		×	×	×	×	×	×	×	×	×		×		×				×	13	10.85	0.94 %	25%	27%	53%	45%	45%	25%	65%
15	13		×	×	×	×	×	×	×	×	×		×	×	×				×	14	8.86	0.72 %	41%	30%	56%	48%	51%	36%	82%
16	12	×	×	×	×	×	×	×	×	×	×		×						×	13	9.77	0.83 %	35%	34%	55%	49%	49%	33%	72%
17	13	×	×	×	×	×	×	×	×	×	×		×	×					×	14	9.06	0.75 %	36%	34%	57%	50%	50%	36%	79%
18	12		×	×	×	×	×	×	×	×	×		×	×					×	13	9.71	0.86 %	35%	45%	57%	54%	50%	39%	69%
19	16		×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	×	17	10.39	0.89 %	5%	26%	46%	42%	36%	13%	63%
20	12		×	×	×	×	×	×	×	×	×	×	×						×	13	10.15	0.90 %	36%	37%	56%	50%	50%	35%	69%

Table 5.6: Modelling details and corresponding accuracy measures of the HSBC forecasting models built using the *BTPs* as an input. The incorporation of the *BTPs* in the modelling improved the forecasting models, compared to the ones ignoring market knowledge. The best model at this step is model 15

Lloyds TSB Models	No. of Input Data	Input Data																		No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
		t-5	t-4	t-3	t-2	t-1	t	5MA	10MA	20MA	40MA	60MA	1st order differencing	Weekly order differencing	RSI one week	RSI two weeks	RSI three weeks	RSI one month	BTPs				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
1	12		×	×	×	×	×	×	×	×	×	×	×						×	13	10.15	1.25 %	46%	46%	55%	54%	52%	40%	75%
2	14	×	×	×	×	×	×	×	×	×	×	×	×	×					×	15	10.65	1.34 %	14%	44%	49%	49%	40%	26%	65%
3	13		×	×	×	×	×	×	×	×	×	×	×	×					×	14	10.04	1.22 %	45%	44%	57%	54%	55%	42%	77%
4	13	×	×	×	×	×	×	×	×	×	×	×	×						×	14	10.11	1.23 %	40%	41%	57%	53%	52%	39%	73%
5	13	×	×	×	×	×	×	×	×	×	×	×		×					×	14	10.69	1.35 %	42%	40%	55%	51%	46%	33%	70%
6	13		×	×	×	×	×	×	×	×	×	×	×		×				×	14	11.08	1.54 %	53%	32%	49%	46%	53%	37%	66%
7	13		×	×	×	×	×	×	×	×	×	×	×			×			×	14	10.92	1.45 %	45%	35%	50%	49%	51%	34%	69%
8	13		×	×	×	×	×	×	×	×	×	×	×				×		×	14	10.80	1.44 %	36%	41%	53%	51%	47%	39%	66%
9	13		×	×	×	×	×	×	×	×	×	×	×					×	×	14	10.72	1.41 %	34%	42%	46%	45%	39%	34%	65%
10	16		×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	×	17	10.55	1.26 %	49%	41%	50%	51%	48%	39%	68%
11	11		×	×	×	×	×	×	×	×	×		×						×	12	9.23	1.10 %	56%	35%	52%	48%	55%	42%	80%
12	12		×	×	×	×	×	×	×	×	×		×	×					×	13	10.66	1.31 %	55%	38%	50%	46%	52%	44%	71%
13	13		×	×	×	×	×	×	×	×	×		×	×	×				×	14	9.92	1.26 %	48%	32%	51%	48%	55%	40%	70%
14	14	×	×	×	×	×	×	×	×	×	×	×	×		×				×	15	10.96	1.49 %	26%	42%	53%	50%	45%	32%	64%
15	15	×	×	×	×	×	×	×	×	×	×	×	×	×	×				×	16	9.86	1.25 %	43%	52%	54%	56%	53%	42%	74%
16	14	×	×	×	×	×	×	×	×	×	×		×	×	×				×	15	10.26	1.41 %	44%	51%	56%	52%	49%	36%	69%
17	11		×	×	×	×	×	×	×	×	×	×							×	12	12.80	1.71 %	0%	7%	57%	42%	39%	4%	50%
18	12		×	×	×	×	×	×	×	×	×	×			×				×	13	11.52	1.59 %	48%	39%	55%	50%	48%	40%	65%
19	12		×	×	×	×	×	×	×	×	×		×		×				×	13	10.10	1.34 %	57%	51%	55%	57%	58%	47%	69%
20	14		×	×	×	×	×	×	×	×	×	×	×	×	×				×	15	9.89	1.23 %	48%	53%	57%	58%	56%	46%	78%

Table 5.7: Modelling details and corresponding accuracy measures of the Lloyds TSB forecasting models built using the *BTPs* as an input. The incorporation of the *BTPs* in the modelling improved the forecasting models, compared to the ones ignoring market knowledge. The best model at this step is model 11

HSBC Models	No. of Input Data	Input Data																		No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
		t-5	t-4	t-3	t-2	t-1	t	5MA	10MA	20MA	40MA	60MA	1^{st} order differencing	Weekly order differencing	RSI one week	RSI two weeks	RSI three weeks	RSI one month	TTPs				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
1	12	×	×	×	×	×	×	×	×	×	×	×							×	13	9.76	0.83 %	55%	54%	52%	55%	55%	47%	75%
2	13	×	×	×	×	×	×	×	×	×	×	×	×						×	14	9.68	0.83 %	57%	56%	47%	54%	54%	46%	79%
3	13	×	×	×	×	×	×	×	×	×	×	×		×					×	14	9.88	0.85 %	58%	54%	49%	54%	55%	47%	77%
4	14	×	×	×	×	×	×	×	×	×	×	×	×	×					×	15	9.61	0.81 %	55%	55%	49%	54%	54%	46%	80%
5	14	×	×	×	×	×	×	×	×	×	×	×	×		×				×	15	10.35	0.91 %	56%	55%	48%	54%	54%	46%	73%
6	14	×	×	×	×	×	×	×	×	×	×	×	×			×			×	15	9.57	0.81 %	55%	55%	47%	53%	53%	45%	80%
7	14	×	×	×	×	×	×	×	×	×	×	×	×				×		×	15	9.42	0.80 %	59%	58%	47%	54%	54%	47%	81%
8	14	×	×	×	×	×	×	×	×	×	×	×	×					×	×	15	9.52	0.80 %	54%	55%	48%	54%	53%	45%	80%
9	17	×	×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	×	18	9.60	0.82 %	55%	57%	47%	54%	53%	46%	78%
10	15	×	×	×	×	×	×	×	×	×	×	×	×	×	×				×	16	10.05	0.84 %	55%	55%	47%	54%	53%	45%	79%
11	14	×	×	×	×	×	×	×	×	×	×		×	×	×				×	15	9.64	0.80 %	54%	54%	49%	54%	54%	45%	81%
12	14		×	×	×	×	×	×	×	×	×	×	×	×	×				×	15	9.67	0.81 %	55%	54%	47%	53%	53%	44%	79%
13	11		×	×	×	×	×	×	×	×	×		×						×	12	9.37	0.78 %	55%	56%	48%	54%	54%	46%	80%
14	12		×	×	×	×	×	×	×	×	×		×		×				×	13	9.92	0.86 %	61%	59%	47%	55%	55%	48%	80%
15	13		×	×	×	×	×	×	×	×	×		×	×	×				×	14	8.62	0.72 %	55%	57%	48%	55%	54%	46%	83%
16	12	×	×	×	×	×	×	×	×	×	×		×						×	13	9.55	0.79 %	55%	56%	47%	54%	53%	45%	81%
17	13	×	×	×	×	×	×	×	×	×	×		×	×					×	14	8.55	0.70 %	57%	57%	47%	54%	54%	46%	89%
18	12		×	×	×	×	×	×	×	×	×		×	×					×	13	9.56	0.80 %	55%	56%	47%	54%	53%	45%	81%
19	16		×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	×	17	9.31	0.79 %	56%	56%	47%	54%	53%	45%	80%
20	12		×	×	×	×	×	×	×	×	×	×	×						×	13	9.47	0.80 %	57%	56%	46%	53%	53%	46%	81%

Table 5.8: Modelling details and corresponding accuracy measures of the HSBC forecasting models built using the *TTPs* as an input. Further improvements were thus achieved, in terms of forecast accuracies, compared to the forecasting models built using the *BTPs*. The best model at this step is model 17

Lloyds TSB Models	No. of Input Data	Input Data																		No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
		t-5	t-4	t-3	t-2	t-1	t	5MA	10MA	20MA	40MA	60MA	1st order differencing	Weekly order differencing	RSI one week	RSI two weeks	RSI three weeks	RSI one month	TTPs				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
1	12		×	×	×	×	×	×	×	×	×	×	×						×	13	10.44	1.33 %	59%	63%	42%	54%	53%	45%	74%
2	14	×	×	×	×	×	×	×	×	×	×	×	×	×					×	15	9.80	1.25 %	61%	63%	40%	53%	52%	45%	75%
3	13		×	×	×	×	×	×	×	×	×	×	×	×					×	14	10.00	1.20 %	58%	59%	44%	55%	54%	44%	82%
4	13	×	×	×	×	×	×	×	×	×	×	×	×						×	14	9.45	1.08 %	55%	58%	49%	56%	55%	45%	83%
5	13	×	×	×	×	×	×	×	×	×	×	×		×					×	14	10.80	1.40 %	54%	58%	47%	55%	53%	44%	69%
6	13		×	×	×	×	×	×	×	×	×	×	×		×				×	14	10.04	1.22 %	60%	61%	46%	56%	55%	46%	74%
7	13		×	×	×	×	×	×	×	×	×	×	×			×			×	14	10.26	1.30 %	55%	60%	44%	53%	52%	41%	69%
8	13		×	×	×	×	×	×	×	×	×	×	×				×		×	14	10.35	1.36 %	54%	59%	48%	52%	56%	42%	72%
9	13		×	×	×	×	×	×	×	×	×	×	×					×	×	14	10.95	1.58 %	59%	61%	42%	51%	55%	38%	75%
10	16		×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	×	17	10.74	1.44 %	57%	62%	45%	56%	54%	41%	74%
11	11		×	×	×	×	×	×	×	×	×		×						×	12	9.52	1.12 %	57%	63%	47%	57%	55%	46%	80%
12	12		×	×	×	×	×	×	×	×	×		×	×					×	13	10.41	1.30 %	59%	63%	42%	54%	53%	46%	76%
13	13		×	×	×	×	×	×	×	×	×		×	×	×				×	14	9.94	1.21 %	58%	60%	44%	59%	56%	48%	77%
14	14	×	×	×	×	×	×	×	×	×	×	×	×		×				×	15	9.35	1.10 %	59%	63%	45%	56%	54%	46%	84%
15	15	×	×	×	×	×	×	×	×	×	×	×	×	×	×				×	16	10.40	1.22 %	51%	57%	49%	55%	53%	43%	76%
16	14	×	×	×	×	×	×	×	×	×	×		×	×	×				×	15	10.65	1.29 %	53%	55%	47%	54%	53%	44%	74%
17	11		×	×	×	×	×	×	×	×	×	×							×	12	10.71	1.71 %	35%	40%	57%	44%	40%	39%	61%
18	12		×	×	×	×	×	×	×	×	×	×			×				×	13	10.66	1.39 %	52%	59%	55%	51%	54%	45%	66%
19	12		×	×	×	×	×	×	×	×	×		×		×				×	13	10.50	1.30 %	58%	62%	45%	55%	54%	46%	76%
20	14		×	×	×	×	×	×	×	×	×	×	×	×	×				×	15	9.41	1.11 %	60%	62%	45%	56%	55%	46%	85%

Table 5.9: Modelling details and corresponding accuracy measures of the Lloyds TSB forecasting models built using the *TTPs* as an input. Further improvements were thus achieved, in terms of forecast accuracies, compared to the forecasting models built using the *BTPs*. The most adequate model at this step is model 11

HSBC Models	No. of Input Data	Input Data																		No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
		t-5	t-4	t-3	t-2	t-1	t	5MA	10MA	20MA	40MA	60MA	1^{st} order differencing	Weekly order differencing	RSI one week	RSI two weeks	RSI three weeks	RSI one month	OMSs				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
1	12	×	×	×	×	×	×	×	×	×	×	×							×	13	6.23	0.51 %	54%	53%	58%	59%	59%	47%	72%
2	13	×	×	×	×	×	×	×	×	×	×	×	×						×	14	6.20	0.51 %	50%	50%	62%	59%	59%	47%	71%
3	13	×	×	×	×	×	×	×	×	×	×	×		×					×	14	6.14	0.51 %	51%	51%	62%	60%	59%	48%	72%
4	14	×	×	×	×	×	×	×	×	×	×	×	×	×					×	15	6.85	0.59 %	51%	51%	59%	58%	58%	47%	70%
5	14	×	×	×	×	×	×	×	×	×	×	×	×		×				×	15	6.32	0.54 %	50%	49%	60%	58%	58%	46%	71%
6	14	×	×	×	×	×	×	×	×	×	×	×	×			×			×	15	6.74	0.59 %	48%	49%	61%	59%	58%	47%	72%
7	14	×	×	×	×	×	×	×	×	×	×	×	×				×		×	15	6.72	0.59 %	50%	49%	60%	58%	58%	46%	72%
8	14	×	×	×	×	×	×	×	×	×	×	×	×					×	×	15	6.65	0.58 %	48%	48%	61%	58%	58%	46%	72%
9	17	×	×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	×	18	5.97	0.50 %	50%	49%	59%	57%	57%	46%	71%
10	15	×	×	×	×	×	×	×	×	×	×	×	×	×	×				×	16	6.31	0.54 %	51%	52%	56%	58%	57%	46%	71%
11	14	×	×	×	×	×	×	×	×	×	×		×	×	×				×	15	6.28	0.53 %	50%	48%	60%	57%	58%	46%	71%
12	14		×	×	×	×	×	×	×	×	×	×	×	×	×				×	15	6.31	0.55 %	52%	50%	62%	60%	60%	48%	71%
13	11		×	×	×	×	×	×	×	×	×		×						×	12	6.77	0.57 %	51%	52%	61%	60%	59%	48%	70%
14	12		×	×	×	×	×	×	×	×	×		×		×				×	13	6.18	0.52 %	50%	51%	60%	59%	58%	47%	71%
15	13		×	×	×	×	×	×	×	×	×		×	×	×				×	14	6.16	0.51 %	51%	50%	59%	58%	58%	46%	71%
16	12	×	×	×	×	×	×	×	×	×	×		×						×	13	6.15	0.52 %	50%	49%	60%	58%	58%	47%	71%
17	13	×	×	×	×	×	×	×	×	×	×		×	×					×	14	6.22	0.51 %	51%	51%	60%	59%	59%	47%	72%
18	12		×	×	×	×	×	×	×	×	×		×	×					×	13	6.29	0.53 %	49%	49%	60%	58%	58%	47%	71%
19	16		×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	×	17	6.03	0.50 %	50%	52%	59%	59%	58%	47%	71%
20	12		×	×	×	×	×	×	×	×	×	×	×						×	13	6.13	0.51 %	50%	51%	59%	58%	58%	46%	72%

Table 5.10: Modelling details and corresponding accuracy measures of the HSBC forecasting models built using the *OMSs* as an input. These models are comparatively similar, in terms of forecast accuracies, to the ones using the *TTPs*. The best model at this step is model 13

Lloyds TSB Models	No. of Input Data	Input Data																		No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
		t-5	t-4	t-3	t-2	t-1	t	5MA	10MA	20MA	40MA	60MA	1st order differencing	Weekly order differencing	RSI one week	RSI two weeks	RSI three weeks	RSI one month	OMSs				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
1	12		×	×	×	×	×	×	×	×	×	×	×						×	13	6.26	0.77 %	50%	56%	58%	60%	58%	47%	70%
2	14	×	×	×	×	×	×	×	×	×	×	×	×	×					×	15	6.59	0.82 %	55%	58%	57%	61%	59%	48%	70%
3	13		×	×	×	×	×	×	×	×	×	×	×	×					×	14	6.45	0.82 %	54%	58%	56%	60%	58%	47%	69%
4	13	×	×	×	×	×	×	×	×	×	×	×	×						×	14	6.50	0.81 %	54%	58%	57%	61%	59%	47%	69%
5	13	×	×	×	×	×	×	×	×	×	×	×		×					×	14	6.56	0.88 %	55%	57%	59%	60%	58%	45%	70%
6	13		×	×	×	×	×	×	×	×	×	×	×		×				×	14	6.66	0.91 %	53%	58%	57%	60%	59%	48%	68%
7	13		×	×	×	×	×	×	×	×	×	×	×			×			×	14	6.46	0.85 %	53%	58%	58%	61%	58%	47%	69%
8	13		×	×	×	×	×	×	×	×	×	×	×				×		×	14	6.50	0.84 %	52%	57%	57%	59%	57%	49%	69%
9	13		×	×	×	×	×	×	×	×	×	×	×					×	×	14	6.72	0.96 %	54%	55%	56%	60%	56%	48%	66%
10	16		×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	×	17	6.17	0.78 %	52%	55%	61%	61%	60%	48%	70%
11	11		×	×	×	×	×	×	×	×	×		×						×	12	6.14	0.75 %	50%	56%	59%	61%	59%	47%	70%
12	12		×	×	×	×	×	×	×	×	×		×	×					×	13	6.90	0.83 %	51%	55%	60%	60%	58%	48%	69%
13	13		×	×	×	×	×	×	×	×	×		×	×	×				×	14	6.62	0.84 %	53%	56%	59%	61%	60%	47%	70%
14	14	×	×	×	×	×	×	×	×	×	×	×	×		×				×	15	6.53	0.82 %	56%	59%	58%	62%	60%	50%	70%
15	15	×	×	×	×	×	×	×	×	×	×	×	×	×	×				×	16	4.72	0.56 %	53%	56%	61%	62%	61%	49%	70%
16	14	×	×	×	×	×	×	×	×	×	×		×	×	×				×	15	6.64	0.82 %	53%	56%	60%	61%	60%	49%	70%
17	11		×	×	×	×	×	×	×	×	×	×							×	12	7.02	0.93 %	50%	52%	56%	60%	58%	47%	66%
18	12		×	×	×	×	×	×	×	×	×	×			×				×	13	6.63	0.89 %	51%	55%	56%	59%	58%	49%	68%
19	12		×	×	×	×	×	×	×	×	×		×		×				×	13	6.50	0.85 %	55%	57%	60%	61%	61%	49%	69%
20	14		×	×	×	×	×	×	×	×	×	×	×	×	×				×	15	6.27	0.78 %	53%	56%	58%	60%	59%	48%	70%

Table 5.11: Modelling details and corresponding accuracy measures of the Lloyds TSB forecasting models built using the *OMSs* as an input. These models are comparatively similar, in terms of forecast accuracies, to the ones using the *TTPs*. The most adequate model at this step in model 11

HSBC Models	No. of Input Data	Input Data																			No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
		t-5	t-4	t-3	t-2	t-1	t	5MA	10MA	20MA	40MA	60MA	1^{st} order differencing	Weekly order differencing	RSI one week	RSI two weeks	RSI three weeks	RSI one month	TTPs	OMSs				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
1	13	×	×	×	×	×	×	×	×	×	×	×							×	×	14	6.11	0.49 %	67%	64%	66%	68%	68%	60%	77%
2	14	×	×	×	×	×	×	×	×	×	×	×	×						×	×	15	6.04	0.50 %	77%	73%	64%	71%	72%	64%	79%
3	14	×	×	×	×	×	×	×	×	×	×	×		×					×	×	15	6.03	0.50 %	76%	71%	62%	69%	70%	62%	78%
4	15	×	×	×	×	×	×	×	×	×	×	×	×	×					×	×	16	6.03	0.49 %	69%	66%	68%	69%	70%	63%	76%
5	15	×	×	×	×	×	×	×	×	×	×	×	×		×				×	×	16	6.09	0.50 %	68%	67%	67%	69%	69%	62%	76%
6	15	×	×	×	×	×	×	×	×	×	×	×	×			×			×	×	16	6.06	0.50 %	69%	67%	68%	69%	70%	63%	76%
7	15	×	×	×	×	×	×	×	×	×	×	×	×				×		×	×	16	6.06	0.49 %	68%	67%	67%	69%	69%	63%	76%
8	15	×	×	×	×	×	×	×	×	×	×	×	×					×	×	×	16	6.08	0.49 %	68%	67%	68%	69%	69%	63%	76%
9	18	×	×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	×	×	19	6.16	0.50 %	70%	69%	65%	69%	69%	62%	79%
10	16	×	×	×	×	×	×	×	×	×	×	×	×	×	×				×	×	17	5.88	0.47 %	75%	73%	65%	71%	72%	64%	79%
11	15	×	×	×	×	×	×	×	×	×	×		×	×	×				×	×	16	6.16	0.51 %	73%	71%	66%	70%	71%	64%	76%
12	15		×	×	×	×	×	×	×	×	×	×	×	×	×				×	×	16	6.53	0.54 %	75%	72%	66%	71%	72%	65%	79%
13	12		×	×	×	×	×	×	×	×	×		×						×	×	13	6.02	0.49 %	70%	71%	65%	70%	69%	62%	77%
14	13		×	×	×	×	×	×	×	×	×		×		×				×	×	14	5.99	0.50 %	74%	70%	65%	70%	71%	63%	78%
15	14		×	×	×	×	×	×	×	×	×		×	×	×				×	×	15	6.21	0.52 %	80%	76%	62%	72%	73%	64%	79%
16	13	×	×	×	×	×	×	×	×	×	×		×						×	×	14	6.07	0.49 %	69%	67%	68%	69%	70%	63%	75%
17	14	×	×	×	×	×	×	×	×	×	×		×	×					×	×	15	6.18	0.51 %	79%	75%	62%	70%	71%	63%	79%
18	13		×	×	×	×	×	×	×	×	×		×	×					×	×	14	6.03	0.49 %	74%	69%	66%	70%	71%	63%	77%
19	17		×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	×	×	18	5.88	0.49 %	64%	64%	66%	67%	67%	59%	76%
20	13		×	×	×	×	×	×	×	×	×	×	×						×	×	14	6.09	0.49 %	69%	66%	69%	70%	70%	64%	77%

Table 5.12: Modelling details and corresponding accuracy measures of the HSBC forecasting models built using both the *TTPs* and the *OMSs* as inputs. These two inputs produced superior forecasting models, compared to the models built solely using the *TTPs* or the *OMSs*. The best model at this step in model 15

Lloyds TSB Models	No. of Input Data	Input Data																			No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
		t-5	t-4	t-3	t-2	t-1	t	5MA	10MA	20MA	40MA	60MA	1st order differencing	Weekly order differencing	RSI one week	RSI two weeks	RSI three weeks	RSI one month	TTPs	OMSs				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
1	13		×	×	×	×	×	×	×	×	×	×	×						×	×	14	4.54	0.50 %	75%	77%	66%	73%	72%	64%	82%
2	15	×	×	×	×	×	×	×	×	×	×	×	×	×					×	×	16	4.60	0.53 %	69%	72%	64%	70%	69%	62%	79%
3	14		×	×	×	×	×	×	×	×	×	×	×	×					×	×	15	6.30	0.77 %	72%	75%	62%	71%	69%	62%	76%
4	14	×	×	×	×	×	×	×	×	×	×	×	×						×	×	15	6.26	0.75 %	76%	77%	65%	73%	72%	64%	77%
5	14	×	×	×	×	×	×	×	×	×	×	×		×					×	×	15	6.34	0.76 %	62%	66%	64%	67%	66%	57%	74%
6	14		×	×	×	×	×	×	×	×	×	×	×		×				×	×	15	6.50	0.78 %	72%	75%	65%	72%	71%	62%	76%
7	14		×	×	×	×	×	×	×	×	×	×	×			×			×	×	15	6.35	0.81 %	69%	72%	62%	70%	69%	60%	75%
8	14		×	×	×	×	×	×	×	×	×	×	×				×		×	×	15	6.51	0.79 %	71%	75%	63%	69%	70%	61%	77%
9	14		×	×	×	×	×	×	×	×	×	×	×					×	×	×	15	6.65	0.83 %	70%	66%	64%	66%	68%	58%	73%
10	17		×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	×	×	18	6.56	0.82 %	73%	75%	66%	72%	71%	64%	76%
11	12		×	×	×	×	×	×	×	×	×		×						×	×	13	6.37	0.79 %	61%	66%	63%	67%	65%	57%	73%
12	13		×	×	×	×	×	×	×	×	×		×	×					×	×	14	5.73	0.69 %	74%	76%	64%	72%	71%	63%	77%
13	14		×	×	×	×	×	×	×	×	×		×	×	×				×	×	15	6.19	0.73 %	71%	71%	66%	70%	70%	63%	77%
14	15	×	×	×	×	×	×	×	×	×	×	×	×		×				×	×	16	6.46	0.76 %	76%	78%	63%	72%	72%	63%	80%
15	16	×	×	×	×	×	×	×	×	×	×	×	×	×	×				×	×	17	4.71	0.52 %	73%	75%	66%	73%	72%	64%	85%
16	15	×	×	×	×	×	×	×	×	×	×		×	×	×				×	×	16	5.07	0.65 %	76%	78%	63%	73%	71%	64%	77%
17	12		×	×	×	×	×	×	×	×	×	×							×	×	13	6.41	0.83 %	63%	67%	64%	68%	66%	58%	71%
18	13		×	×	×	×	×	×	×	×	×	×			×				×	×	14	6.44	0.77 %	65%	63%	62%	66%	66%	56%	73%
19	13		×	×	×	×	×	×	×	×	×		×		×				×	×	14	5.56	0.65 %	72%	74%	62%	71%	70%	61%	80%
20	15		×	×	×	×	×	×	×	×	×	×	×	×	×				×	×	16	6.27	0.78 %	79%	82%	58%	72%	71%	62%	79%

Table 5.13: Modelling details and corresponding accuracy measures of the Lloyds TSB forecasting models built using both the *TTPs* and the *OMSs* as inputs. These two inputs produced superior forecasting models, compared to the models built solely using the *OMSs*. The best model at this step in model 1

RBS Models	No. of Input Data	Input Data																			No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
		t-5	t-4	t-3	t-2	t-1	t	5MA	10MA	20MA	40MA	60MA	1st order differencing	Weekly order differencing	RSI one week	RSI two weeks	RSI three weeks	RSI one month	TTPs	OMSs				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
1	12		×	×	×	×	×	×	×	×	×	×							×	×	13	13.01	0.53 %	73%	72%	70%	70%	69%	64%	81%
2	13		×	×	×	×	×	×	×	×	×	×	×						×	×	14	12.75	0.51 %	72%	72%	63%	69%	69%	63%	83%
3	15	×	×	×	×	×	×	×	×	×	×	×	×	×					×	×	16	12.79	0.51 %	72%	71%	64%	69%	69%	64%	82%
4	12		×	×	×	×	×	×	×	×	×		×						×	×	12	12.85	0.53 %	72%	68%	65%	68%	69%	64%	81%
5	14		×	×	×	×	×	×	×	×	×	×	×		×				×	×	15	13.03	0.54 %	77%	76%	64%	72%	72%	66%	82%
6	16	×	×	×	×	×	×	×	×	×	×	×	×	×	×				×	×	17	12.47	0.51 %	74%	73%	65%	71%	71%	65%	83%
7	15	×	×	×	×	×	×	×	×	×	×		×	×	×				×	×	16	12.68	0.53 %	77%	76%	61%	71%	70%	64%	83%
8	14	×	×	×	×	×	×	×	×	×			×	×	×				×	×	15	14.43	0.55 %	70%	68%	62%	66%	67%	62%	82%
9	15	×	×	×	×	×	×	×	×	×	×		×	×		×			×	×	16	12.69	0.53 %	75%	75%	61%	70%	69%	64%	84%
10	15	×	×	×	×	×	×	×	×	×	×		×	×			×		×	×	16	12.94	0.54 %	70%	69%	60%	69%	69%	63%	80%
11	15	×	×	×	×	×	×	×	×	×	×		×	×				×	×	×	16	12.89	0.53 %	71%	70%	61%	70%	68%	62%	81%
12	16	×	×	×	×	×	×	×	×	×	×		×	×	×	×			×	×	17	12.47	0.52 %	75%	74%	61%	70%	69%	64%	84%
13	14		×	×	×	×	×	×	×	×	×		×	×	×				×	×	15	13.04	0.54 %	74%	72%	63%	69%	70%	64%	81%
14	13		×	×	×	×	×	×	×	×	×		×		×				×	×	14	12.33	0.50 %	74%	72%	65%	71%	70%	66%	83%
15	14		×	×	×	×	×	×	×	×	×		×		×	×			×	×	15	12.77	0.53 %	77%	76%	60%	70%	70%	63%	83%
16	12		×	×	×	×	×	×	×	×			×		×				×	×	13	15.30	0.57 %	64%	68%	63%	66%	64%	61%	79%
17	12			×	×	×	×	×	×	×	×		×		×				×	×	13	12.64	0.52 %	72%	73%	63%	70%	69%	64%	82%
18	12		×	×	×	×	×	×	×	×			×		×				×	×	13	15.30	0.57 %	64%	68%	63%	66%	64%	61%	79%
19	13			×	×	×	×	×	×	×	×	×	×		×				×	×	14	12.25	0.50 %	73%	72%	64%	70%	70%	65%	83%
20	12			×	×	×	×	×	×	×	×		×		×				×	×	13	12.43	0.52 %	70%	71%	64%	69%	68%	64%	82%

Table 5.14: Modelling details and corresponding accuracy measures of the RBS forecasting models built using both the *TTPs* and the *OMSs* as inputs. These two inputs systematically generated superior forecasting models. The most adequate model at this step is model 14

HSBC Models	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
			Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
daily *OMSs*	6.21	0.52%	80%	76%	62%	72%	73%	64%	79%
weekly *OMSs*	9.45	0.81%	56%	53%	49%	53%	54%	46%	77%
bi-weekly *OMSs*	10.29	0.91%	59%	57%	47%	54%	55%	47%	77%
monthly *OMSs*	10.92	1.05%	55%	51%	44%	50%	54%	46%	75%

Table 5.15: The accuracy measures of the HSBC forecasting models built using the lower frequencies of the *OMSs*. It can be seen that the forecasting models, built using the three periods of the *OMSs* (weekly, bi-weekly and monthly), produced accuracy measures lower than the accuracy measures generated using the daily *OMSs*

Lloyds TSB Models	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
			Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
daily *OMSs*	4.54	0.50%	75%	77%	66%	73%	72%	64%	82%
weekly *OMSs*	10.23	1.02%	55%	54%	44%	51%	58%	49%	75%
bi-weekly *OMSs*	10.86	1.17%	56%	54%	46%	53%	53%	48%	75%
monthly *OMSs*	11.23	1.29%	52%	50%	46%	55%	56%	48%	72%

Table 5.16: The accuracy measures of the Lloyds TSB forecasting models built using the lower frequencies of the *OMSs*. This table shows that the forecasting model, built using the daily *OMSs*, outperformed the forecasting models, built using the weekly, bi-weekly and monthly *OMSs*, in terms of all accuracy measures employed in this research

RBS Models	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
			Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
daily *OMSs*	12.33	0.50%	74%	72%	65%	71%	70%	66%	83%
weekly *OMSs*	14.64	0.89%	49%	51%	41%	58%	54%	44%	76%
bi-weekly *OMSs*	15.02	1.14%	51%	51%	44%	52%	55%	47%	77%
monthly *OMSs*	15.39	1.22%	50%	52%	46%	50%	52%	46%	73%

Table 5.17: The accuracy measures of the RBS forecasting models built using the lower frequencies of the *OMSs*. This table shows that these inputs (weekly, bi-weekly and monthly *OMSs*) reduce the quality of the forecasting models, compared to the forecasting model built using the daily *OMSs*, in terms of all accuracy measures employed in this research

HSBC Models	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
			Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
original daily *OMSs*	6.21	0.52%	80%	76%	62%	72%	73%	64%	79%
daily *OMSs* include a wrong investment decision of 2% (ND with μ=0 and σ=0.2)	6.32	0.53%	75%	72%	66%	71%	72%	63%	76%
daily *OMSs* include a wrong investment decision of 9% (ND with μ=0 and σ=0.3)	6.55	0.55%	75%	74%	62%	70%	70%	62%	79%
daily *OMSs* include a wrong investment decision of 20% (ND with μ=0 and σ=0.4)	6.83	0.58%	72%	71%	63%	69%	69%	61%	77%
daily *OMSs* include a wrong investment decision of 30% (ND with μ=0 and σ=0.5)	6.92	0.58%	69%	68%	62%	67%	67%	59%	79%

Table 5.18: The accuracy measures of the HSBC forecasting models built using the *OMSs* included a wrong investment decision. It can be seen that the forecasting model built using the *OMSs* included a wrong investment decision of 30% produced adequate accuracy measures compared to the concluding forecasting model built using just the *TTPs* and *OMSs* separately, shown in Tables 5.8 and 5.10 respectively

Lloyds TSB Models	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
			Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
original daily *OMSs*	4.54	0.50%	75%	77%	66%	73%	72%	64%	82%
daily *OMSs* include a wrong investment decision of 2% (ND with μ=0 and σ=0.2)	6.39	0.78%	72%	72%	61%	69%	69%	60%	77%
daily *OMSs* include a wrong investment decision of 9% (ND with μ=0 and σ=0.3)	6.58	0.81%	58%	61%	60%	63%	62%	52%	73%
daily *OMSs* include a wrong investment decision of 20% (ND with μ=0 and σ=0.4)	7.08	0.85%	64%	66%	59%	65%	64%	55%	75%
daily *OMSs* include a wrong investment decision of 30% (ND with μ=0 and σ=0.5)	7.00	0.85%	64%	66%	59%	66%	65%	54%	76%

Table 5.19: The accuracy measures of the Lloyds TSB forecasting models built using the *OMSs* included a wrong investment decision. This table shows that the accuracy measures obtained from the forecasting model built using the *OMSs* included a wrong investment decision of 30% were adequate compared to the concluding forecasting model built using just the *TTPs* and the *OMSs* separately as a new input, shown in Tables 5.9 and 5.11 respectively

RBS Models	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
			Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
original daily *OMSs*	12.33	0.50%	74%	72%	65%	71%	70%	66%	83%
daily *OMSs* include a wrong investment decision of 2% (ND with μ=0 and σ=0.2)	13.83	0.56%	70%	72%	60%	68%	67%	61%	82%
daily *OMSs* include a wrong investment decision of 9% (ND with μ=0 and σ=0.3)	14.31	0.60%	68%	67%	63%	66%	66%	61%	81%
daily *OMSs* include a wrong investment decision of 20% (ND with μ=0 and σ=0.4)	14.64	0.63%	70%	68%	57%	65%	65%	59%	80%
daily *OMSs* include a wrong investment decision of 30% (ND with μ=0 and σ=0.5)	16.14	0.71%	73%	69%	57%	65%	66%	59%	81%

Table 5.20: The accuracy measures of the RBS forecasting models built using the *OMSs* included a wrong investment decision. Using the *OMSs* included a wrong investment decision of 30% produced adequate forecasting model compared to the concluding forecasting models for HSBC and Lloyds TSB, shown in Tables 5.18 and 5.19 respectively

HSBC Models	No. of Input Data	Input Data														No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
		t-4	t-3	t-2	t-1	t	5MA	10MA	20MA	40MA	1^{st} order differencing	Weekly order differencing	RSI one week	TTPs	OMSs				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
	14	×	×	×	×	×	×	×	×	×	×	×	×	×	×	15	6.92	0.58%	69%	68%	62%	67%	67%	59%	79%
1	13		×	×	×	×	×	×	×	×	×	×	×	×	×	14	6.86	0.58%	71%	68%	62%	67%	68%	60%	80%
2	12			×	×	×	×	×	×	×	×	×	×	×	×	13	7.30	0.63%	64%	65%	64%	66%	66%	58%	75%
3	12		×		×	×	×	×	×	×	×	×	×	×	×	13	7.25	0.63%	63%	63%	63%	65%	65%	57%	75%
4	12		×	×		×	×	×	×	×	×	×	×	×	×	13	7.33	0.64%	62%	62%	60%	66%	64%	57%	74%
5	12		×	×	×	×		×	×	×	×	×	×	×	×	13	6.91	0.58%	65%	66%	62%	67%	66%	58%	78%
6	12		×	×	×	×	×		×	×	×	×	×	×	×	13	6.91	0.59%	64%	65%	63%	66%	66%	58%	79%
7	12		×	×	×	×	×	×		×	×	×	×	×	×	13	6.93	0.59%	65%	63%	63%	65%	65%	56%	77%
8	12		×	×	×	×	×	×	×		×	×	×	×	×	13	6.94	0.58%	67%	67%	62%	67%	67%	58%	79%
9	12		×	×	×	×	×	×	×	×	×		×	×	×	13	6.96	0.59%	66%	66%	63%	67%	66%	59%	79%
10	12		×	×	×	×	×	×	×	×	×	×		×	×	13	6.95	0.59%	63%	63%	63%	65%	65%	57%	78%

Table 5.21: Modelling details and corresponding accuracy measures of the HSBC obtained in the refinement step of the forecasting model. This table shows that the historic open share prices for four days before, y_{t-1}, was non-significant input used when building the forecasting models for HSBC, as shown in the forecasting model number 1

Lloyds TSB Models	No. of Input Data	Input Data													No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
		t-4	t-3	t-2	t-1	t	5MA	10MA	20MA	40MA	60MA	1st order differencing	TTPs	OMSs				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
	13	×	×	×	×	×	×	×	×	×	×	×	×	×	14	7.00	0.85%	64%	66%	59%	66%	65%	54%	76%
1	12		×	×	×	×	×	×	×	×	×	×	×	×	13	7.44	0.92%	65%	70%	58%	67%	65%	54%	74%
2	12	×		×	×	×	×	×	×	×	×	×	×	×	13	7.35	0.92%	66%	70%	58%	67%	66%	55%	75%
3	12	×	×		×	×	×	×	×	×	×	×	×	×	13	7.36	0.92%	64%	69%	57%	66%	65%	54%	74%
4	12	×	×	×		×	×	×	×	×	×	×	×	×	13	7.42	0.93%	65%	65%	58%	67%	65%	54%	75%
5	12	×	×	×	×	×		×	×	×	×	×	×	×	13	7.34	0.91%	65%	70%	58%	67%	65%	55%	75%
6	12	×	×	×	×	×	×		×	×	×	×	×	×	13	7.36	0.92%	63%	65%	56%	66%	65%	56%	74%
7	12	×	×	×	×	×	×	×		×	×	×	×	×	13	7.33	0.92%	64%	64%	55%	66%	65%	55%	75%
8	12	×	×	×	×	×	×	×	×		×	×	×	×	13	7.40	0.93%	63%	64%	55%	65%	65%	54%	75%
9	12	×	×	×	×	×	×	×	×	×		×	×	×	13	7.08	0.87%	65%	68%	59%	66%	65%	54%	75%
10	11	×	×	×	×	×	×	×	×	×			×	×	12	7.51	0.94%	61%	60%	55%	62%	62%	54%	74%

Table 5.22: Modelling details and corresponding accuracy measures of the Lloyds TSB obtained in the refinement step of the forecasting model. It can be seen that the moving average for three months, 60MA, was non-significant input can be used when building the forecasting models for Lloyds TSB, as shown in the forecasting model number 9 which is generated comparable accuracy measures with the concluding models obtained in the previous step

RBS Models	No. of Input Data	Input Data: t-4	t-3	t-2	t-1	t	5MA	10MA	20MA	40MA	1st order differencing	RSI one week	TTPs	OMSs	No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points: Maxima (NX)	Minima (NN)	Not TPs (NP)	Specificity of Predicted Turning Points: Maxima (PX)	Minima (PN)	Not TPs (PP)	Direction of Shares (DoS)
	13	×	×	×	×	×	×	×	×	×	×	×	×	×	14	16.14	0.71%	73%	69%	57%	65%	66%	59%	81%
1	12		×	×	×	×	×	×	×	×	×	×	×	×	13	16.47	0.72%	73%	70%	56%	65%	66%	59%	82%
2	11			×	×	×	×	×	×	×	×	×	×	×	12	16.64	0.72%	71%	66%	57%	64%	65%	58%	80%
3	11		×		×	×	×	×	×	×	×	×	×	×	12	16.62	0.72%	70%	66%	56%	64%	64%	58%	79%
4	11		×	×		×	×	×	×	×	×	×	×	×	12	16.70	0.73%	69%	66%	56%	63%	63%	57%	79%
5	11		×	×	×	×		×	×	×	×	×	×	×	12	16.75	0.75%	66%	65%	55%	62%	63%	57%	78%
6	11		×	×	×	×	×		×	×	×	×	×	×	12	16.74	0.74%	67%	65%	56%	63%	63%	58%	80%
7	11		×	×	×	×	×	×		×	×	×	×	×	12	16.72	0.73%	68%	66%	57%	64%	64%	58%	80%
8	11		×	×	×	×	×	×	×		×	×	×	×	12	16.69	0.72%	70%	69%	57%	64%	65%	58%	80%
9	11		×	×	×	×	×	×	×	×		×	×	×	12	16.77	0.76%	68%	67%	56%	63%	63%	57%	79%
10	11		×	×	×	×	×	×	×	×	×		×	×	12	16.59	0.72%	73%	69%	58%	66%	66%	60%	80%

Table 5.23: Modelling details and corresponding accuracy measures of the RBS obtained in the refinement step of the forecasting model. This step shows that both the historic open share prices four days before, y_{t-4}, and the *RSI* technical indicator for one week were non-significant inputs can be used for modelling the share prices of the RBS, as shown in the forecasting model number 10 which is generated comparable accuracy measures with the most adequate model obtained in the previous step

HSBC Models	No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
	14	6.86	0.58%	71%	68%	62%	67%	68%	60%	80%
1	13	7.04	0.59%	66%	62%	61%	64%	65%	57%	78%
2	12	7.26	0.61%	69%	67%	61%	66%	67%	59%	79%
3	11	7.19	0.61%	68%	65%	62%	66%	67%	59%	78%
4	10	7.15	0.60%	71%	68%	63%	68%	68%	61%	78%
5	9	7.50	0.66%	66%	64%	61%	65%	65%	57%	77%

Table 5.24: The accuracy measures, employed in this research, of HSBC forecasting models obtained when reducing the number of neurons in hidden layer of concluding model. This table shows that the forecasting model with 10 neurons in one hidden layer was selected as a concluding model to forecast the future share prices of HSBC Bank

Lloyds TSB Models	No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
	13	7.08	0.87%	65%	68%	59%	66%	65%	54%	75%
1	12	6.74	0.86%	71%	75%	58%	69%	67%	57%	78%
2	11	7.29	0.93%	69%	71%	58%	68%	67%	55%	76%
3	10	7.31	0.93%	63%	65%	57%	64%	63%	52%	73%
4	9	7.27	0.95%	62%	64%	58%	64%	63%	52%	72%

Table 5.25: The accuracy measures of the forecasting models for Lloyds TSB obtained when reducing the number of neurons in hidden layer of concluding model obtained in the previous step. The forecasting model with 12 neurons in one hidden layer was outperformed the concluding model obtained in the previous step and, hence, was selected as a concluding model to forecast the future share prices of Lloyds TSB

RBS Models	No. of Neurons in One Hidden Layer	RMSE	MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
				Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
	12	16.59	0.72%	73%	69%	58%	66%	66%	60%	80%
1	11	15.73	0.68%	67%	64%	61%	64%	65%	59%	80%
2	10	15.94	0.68%	71%	67%	58%	65%	65%	59%	81%
3	9	15.95	0.69%	70%	64%	58%	64%	65%	59%	81%
4	8	15.86	0.68%	70%	65%	57%	63%	65%	58%	81%

Table 5.26: The accuracy measures of RBS forecasting models obtained when reducing the number of neurons in hidden layer of concluding model obtained in the previous step. It can be seen that the forecasting model with 10 neurons in one hidden layer was selected as a concluding model to forecast the future share prices of RBS

Banks		MAPE	Sensitivity of Predicted Turning Points			Specificity of Predicted Turning Points			Direction of Shares (DoS)
			Maxima (NX)	Minima (NN)	Not TPs (NP)	Maxima (PX)	Minima (PN)	Not TPs (PP)	
HSBC	Concluding Model	0.60%	71%	68%	63%	68%	68%	61%	78%
	Testing the Model	0.64%	74%	70%	47%	61%	63%	50%	74%
Lloyds TSB	Concluding Model	0.86%	71%	75%	58%	69%	67%	57%	78%
	Testing the Model	0.87%	56%	62%	54%	60%	60%	47%	68%
RBS	Concluding Model	0.68%	71%	67%	58%	65%	65%	59%	81%
	Testing the Model	0.87%	57%	56%	59%	58%	59%	56%	60%

Table 5.27: The accuracy measures of testing the concluding forecasting model for HSBC, Lloyds TSB and RBS. It can be seen that the concluding forecasting model of each bank gives comparable accuracy measures with the concluding trained model

Figure 5.1: The historic daily open share prices of HSBC Bank which covers the period from 3rd July 2000 until 30th March 2007. This figure shows that the share price suffers high volatilities in its movement

Figure 5.2: The historic daily open share prices of Lloyds TSB Bank which covers the period from 3rd July 2000 until 30th March 2007. This figure shows high volatility in the share price movement

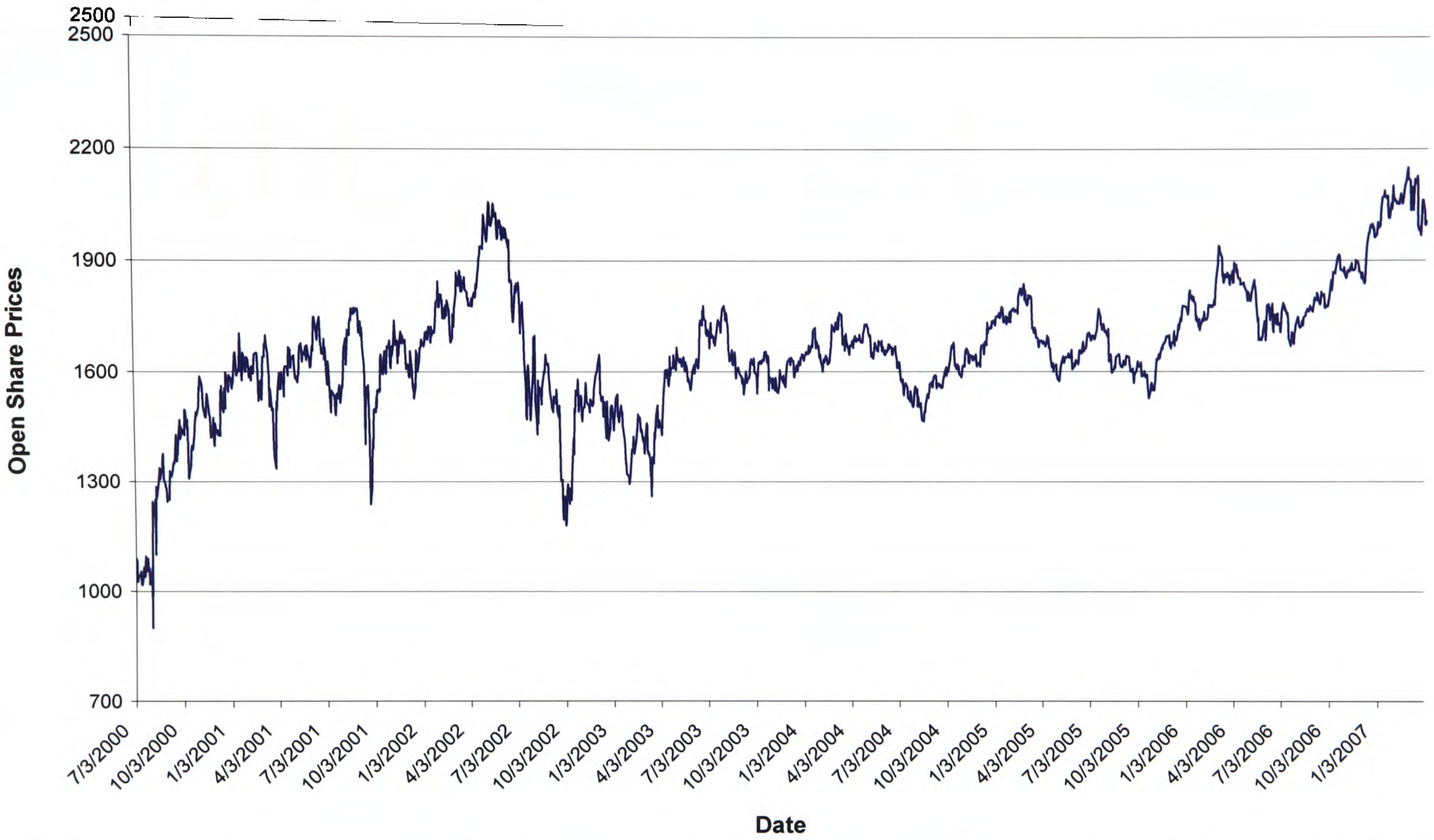

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Figure 5.3: The historic daily open share prices of Royal Bank of Scotland which covers the period from 3rd July 2000 until 30th March 2007. This figure shows that a high volatility in the share price movement

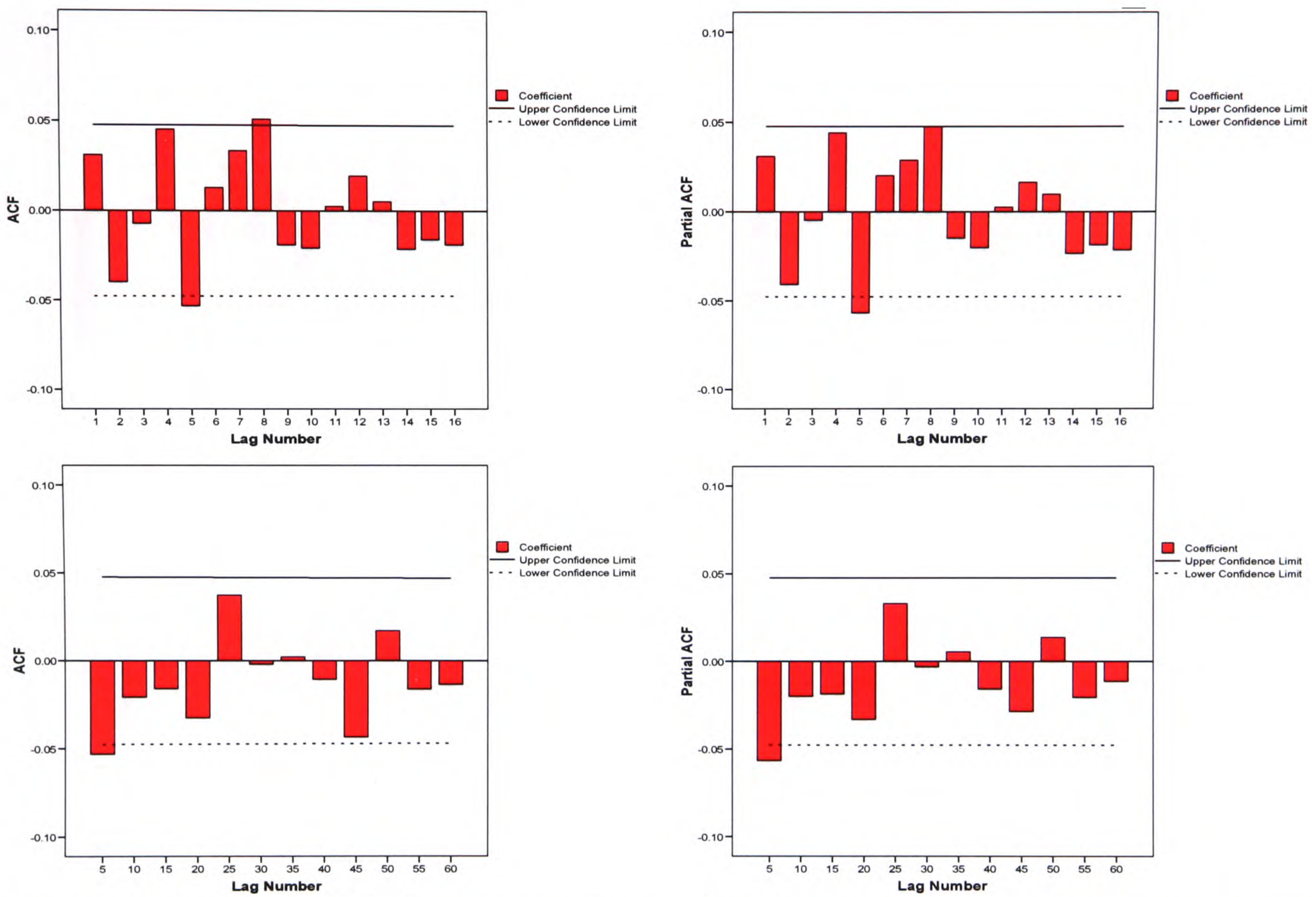

Figure 5.4: The ACF & PACF of the differenced open share prices for HSBC Bank at non-seasonal lags (Top) and seasonal lags (Bottom). This figure shows that there is a weekly seasonality for the dataset of HSBC Bank

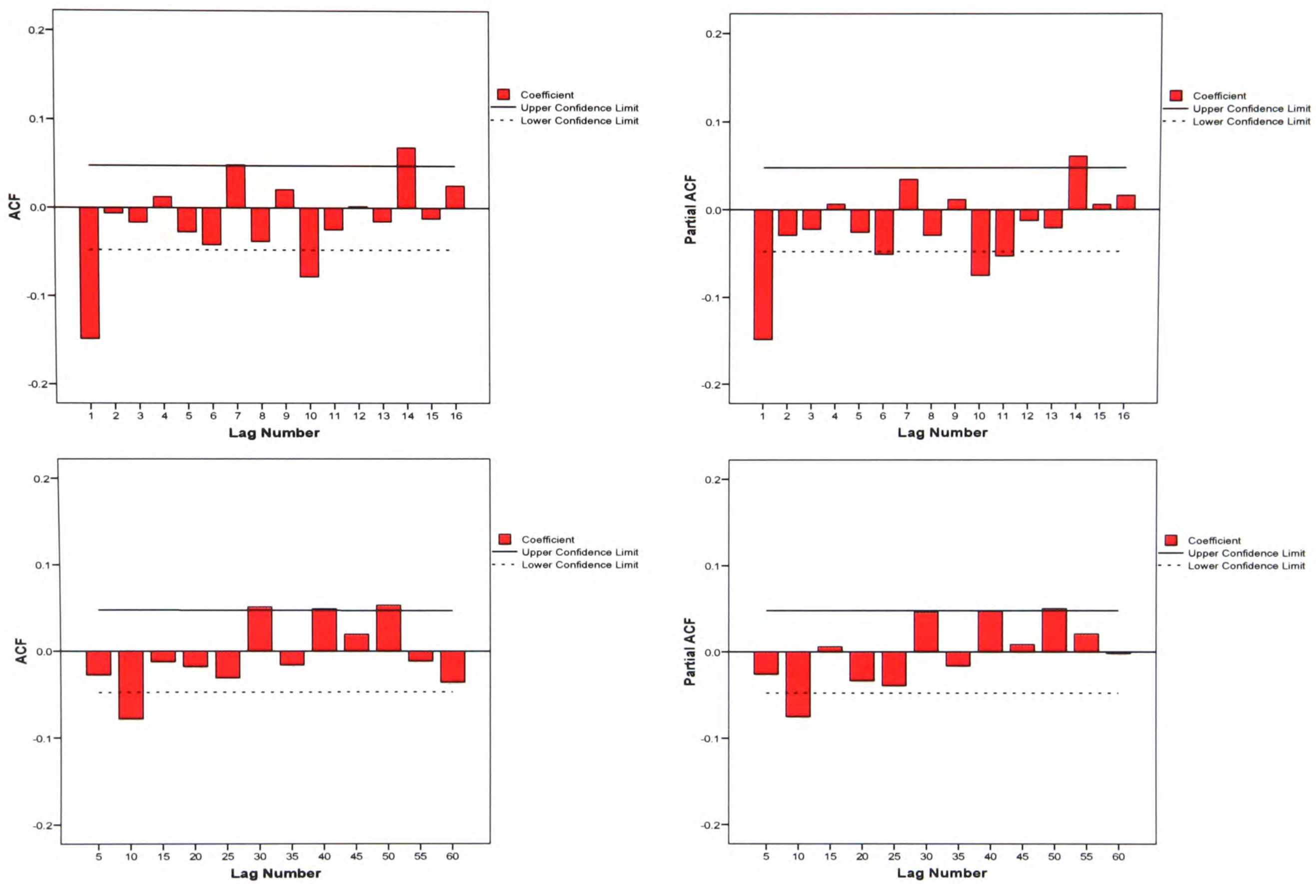

Figure 5.5: The ACF & PACF of the differenced open share prices for Lloyds TSB Bank at non-seasonal lags (Top) and seasonal lags (Bottom). A bi-weekly seasonality may be present in this dataset

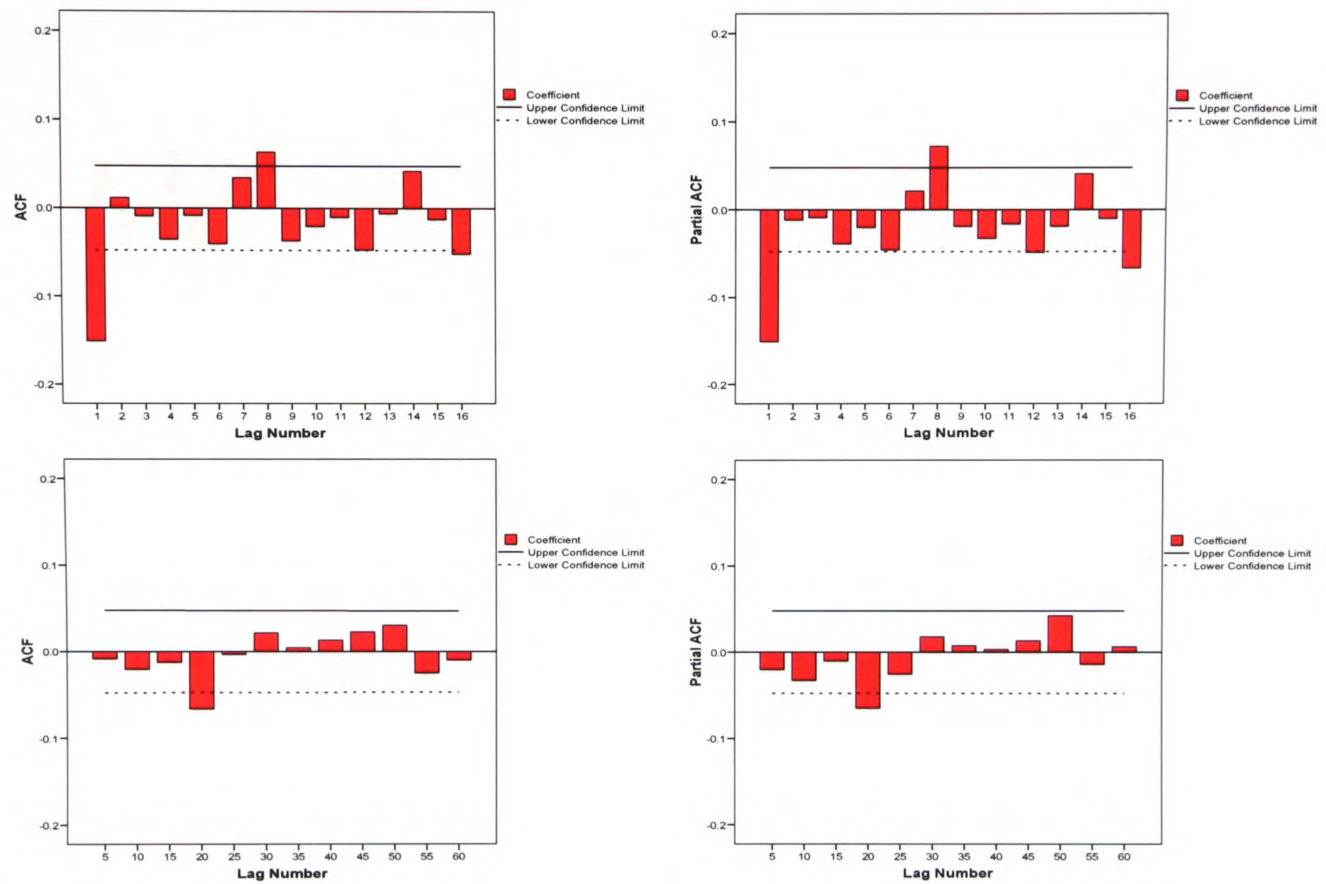

Figure 5.6: The ACF & PACF of the differenced open share prices for RBS at non-seasonal lags (Top) and seasonal lags (Bottom). It shows that there is monthly seasonality is detected in the dataset of RBS

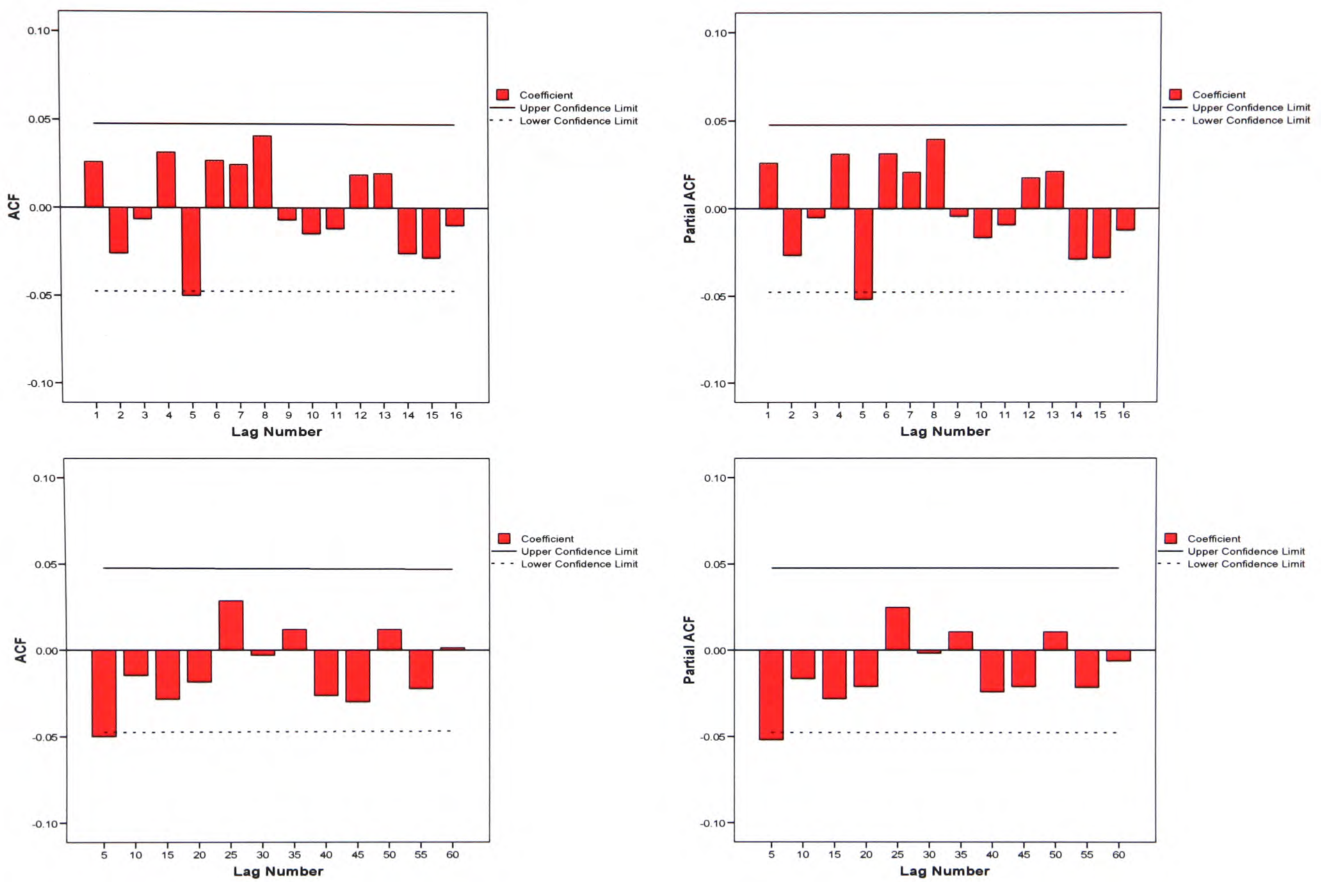

Figure 5.7: The ACF & PACF of the residuals obtained form the concluding forecasting model of HSBC Bank using GARCH model at non-seasonal lags (Top) and seasonal lags (Bottom). It can be seen that there is no evidence of non-randomness is the errors. Hence, this suggests that the model is adequate and can be used for forecasting

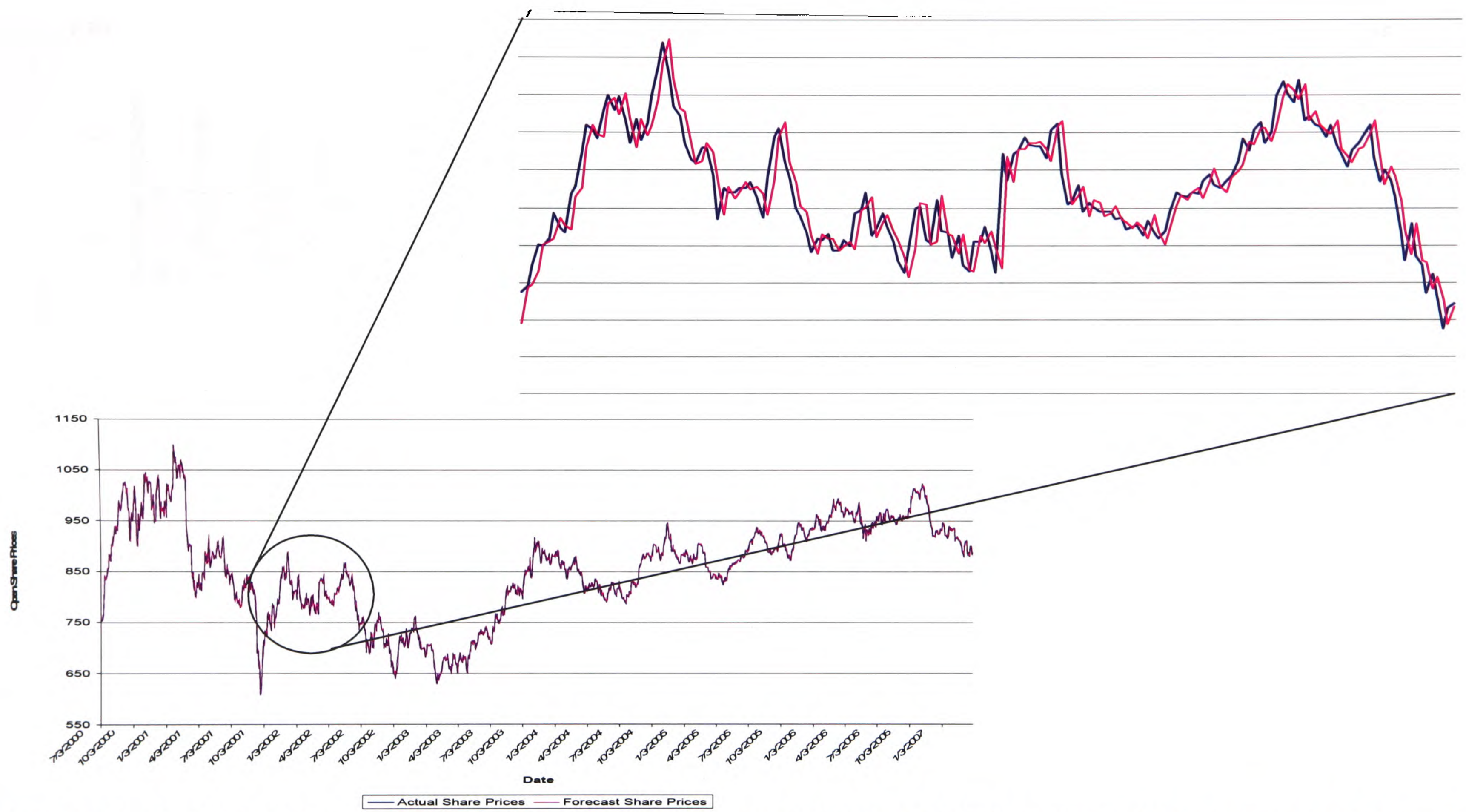

Figure 5.8: Actual and forecast daily open share prices of the HSBC Bank Plc using GARCH model. This figure occasionally shows a one day lag between the actual and the forecast values

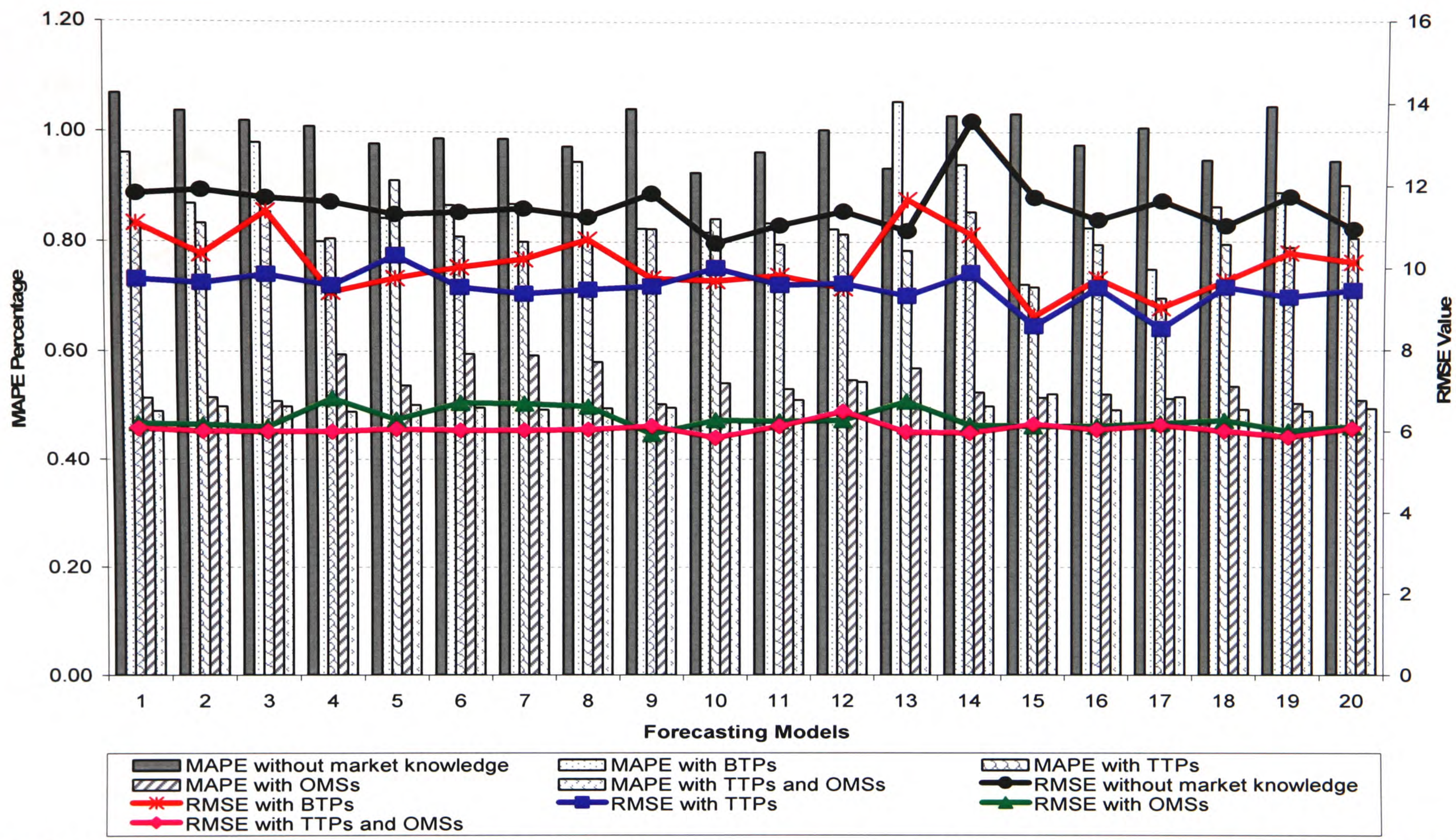

Figure 5.9: The RMSE and the MAPE of the forecasting models of the whole modelling steps for HSBC Bank. The figure shows that the forecasting models built using both the *TTPs* and *OMSs* as inputs outperformed other forecasting models

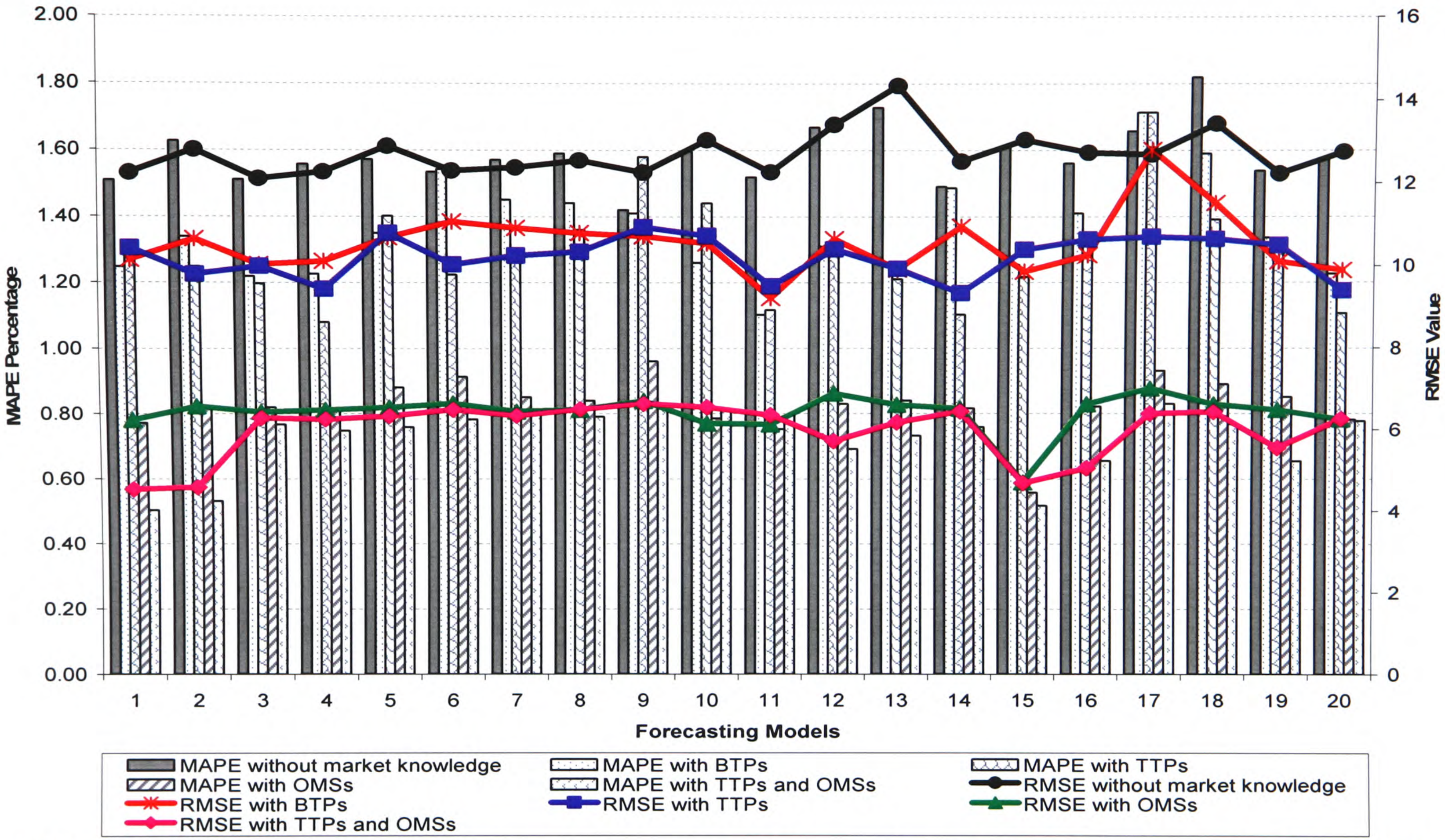

Figure 5.10: The RMSE and the MAPE of the forecasting models of the whole modelling steps for Lloyds TSB. The figure shows that the forecasting models built using both the *TTPs* and *OMSs* as inputs outperformed other forecasting models

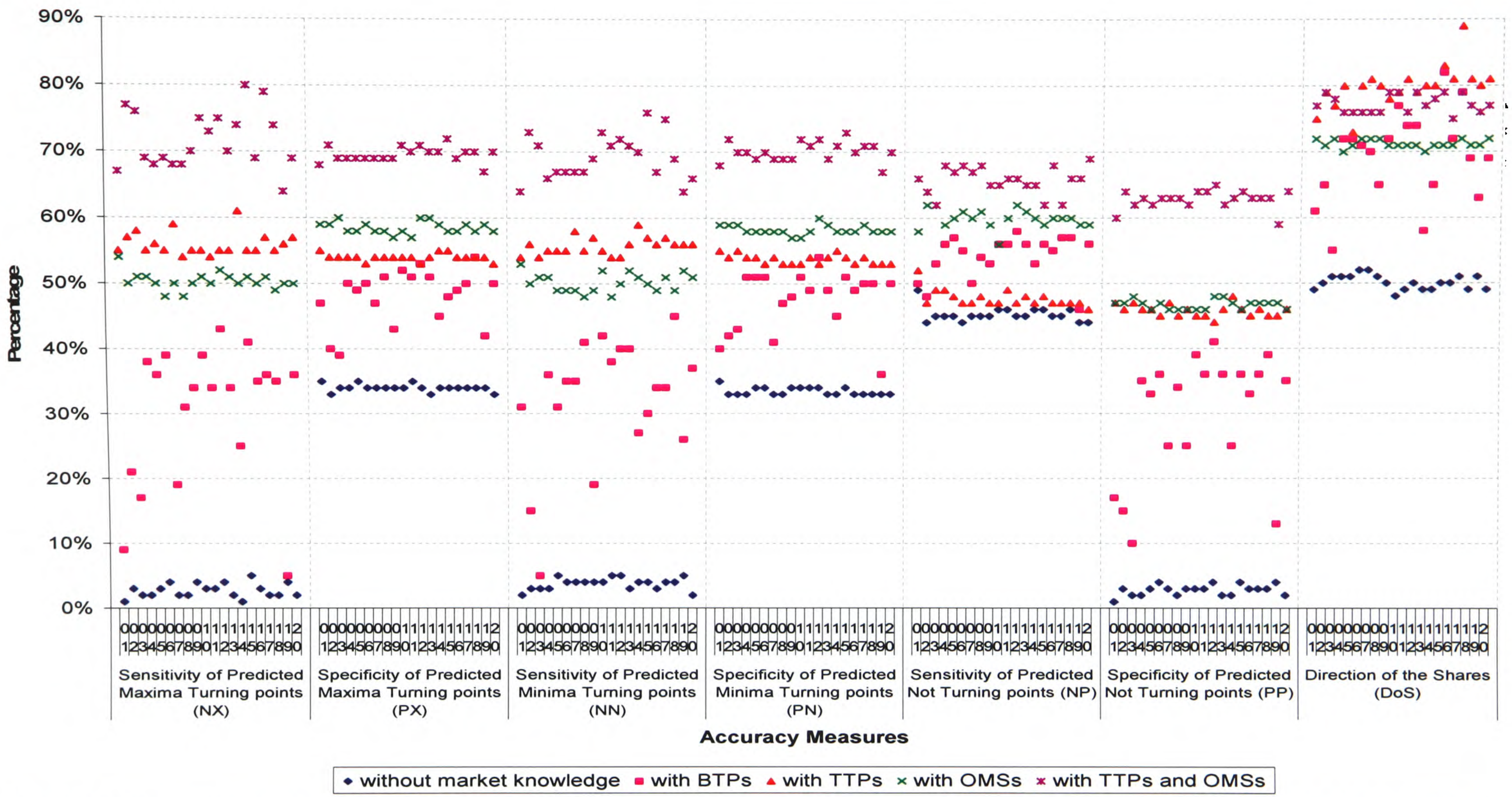

Figure 5.11: The sensitivity and specificity of predicted turning points (maxima, minima and 'not turning points') and the direction of the shares of the forecasting models of the whole modelling steps for HSBC Bank. The figure shows that the forecasting models built using the *TTPs* and *OMSs* together as inputs outperformed other forecasting models

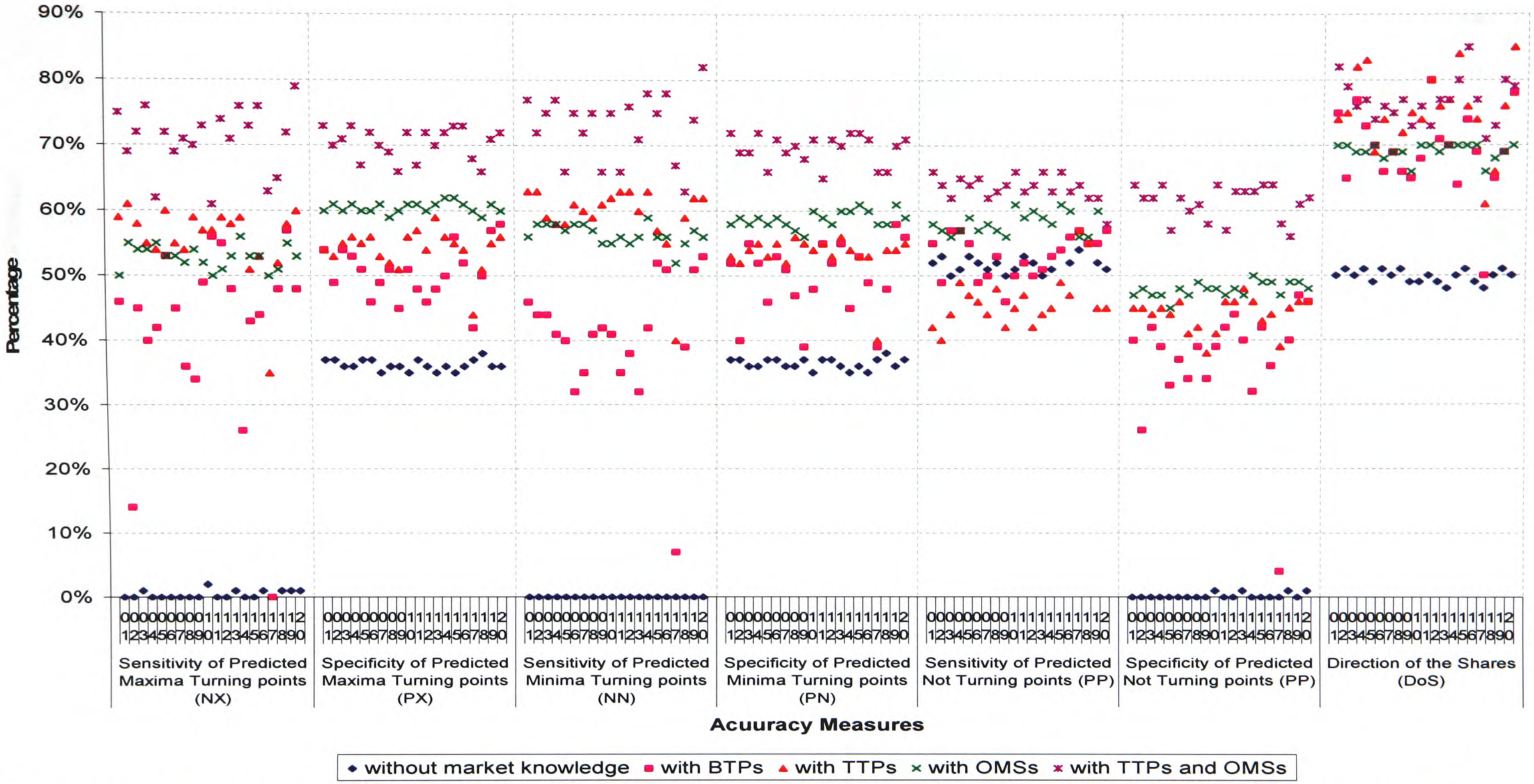

Figure 5.12: The sensitivity and specificity of predicted turning points (maxima, minima and 'not turning points') and the direction of the shares of the forecasting models of the whole modelling steps for Lloyds TSB. The figure shows that the forecasting models built using the *TTPs* and *OMSs* together as inputs outperformed other forecasting models

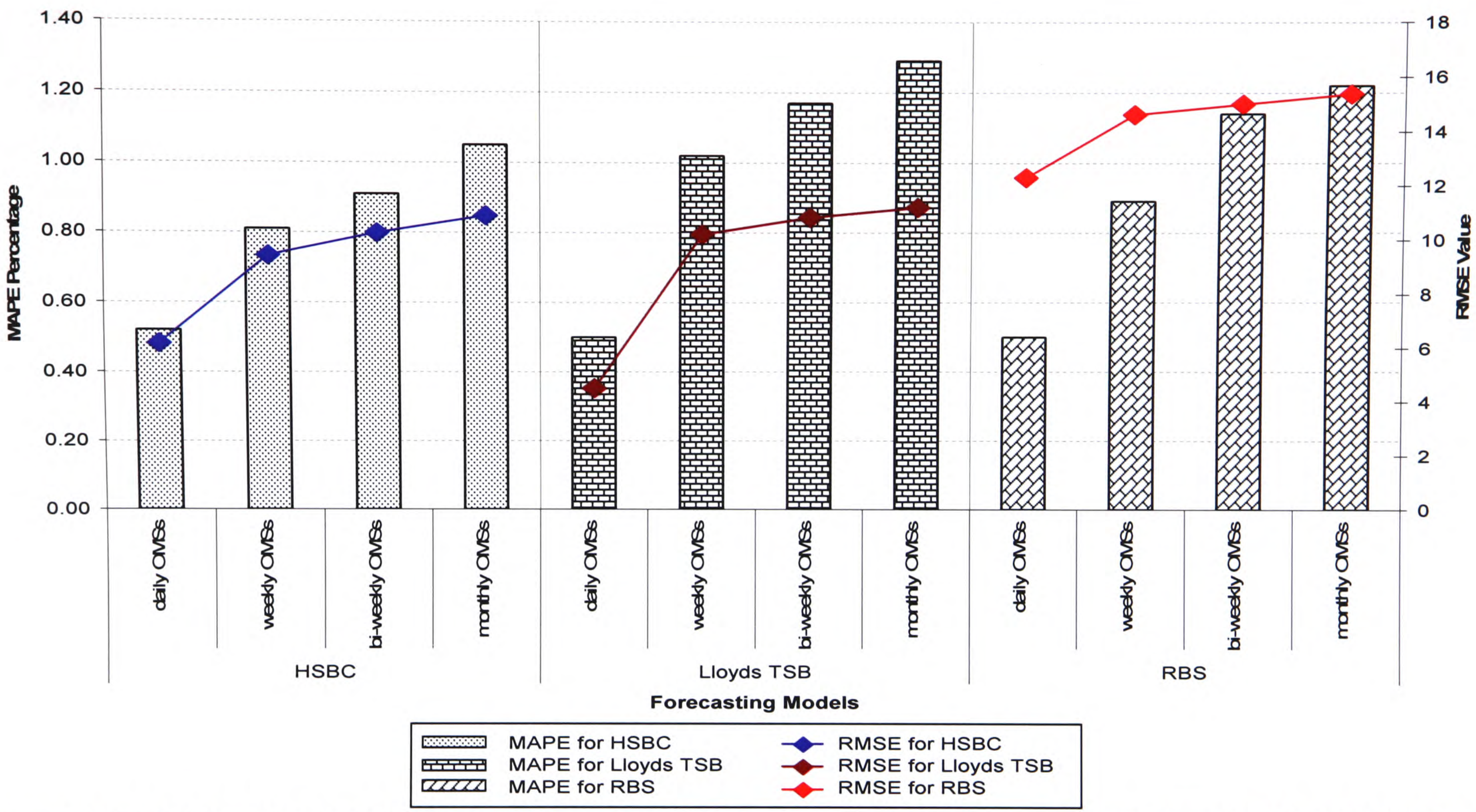

Figure 5.13: The RMSE and the MAPE of the forecasting models for HSBC, Lloyds TSB and RBS built using the lower frequencies of the *OMSs*. The figure shows that the forecasting models built using the daily *OMSs* outperformed the forecasting models built using the lower frequencies of the *OMSs*

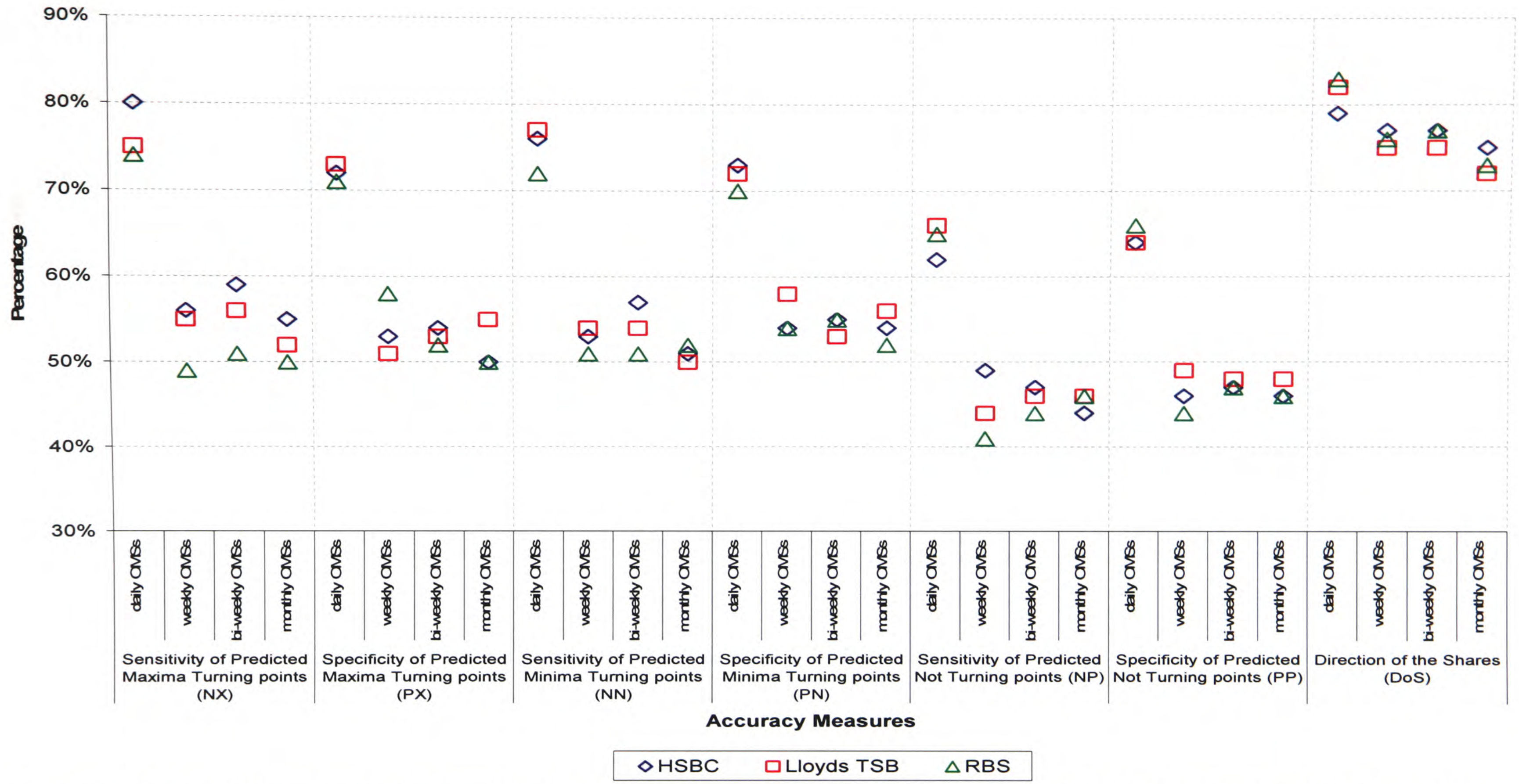

Figure 5.14: The sensitivity and specificity of predicted turning points (maxima, minima and 'not turning points') and the direction of the shares of the forecasting models for HSBC, Lloyds TSB and RBS built using the lower frequencies of the *OMSs*. The figure shows that the forecasting models built using the daily *OMSs* outperformed the forecasting models built using the lower frequencies of the *OMSs*

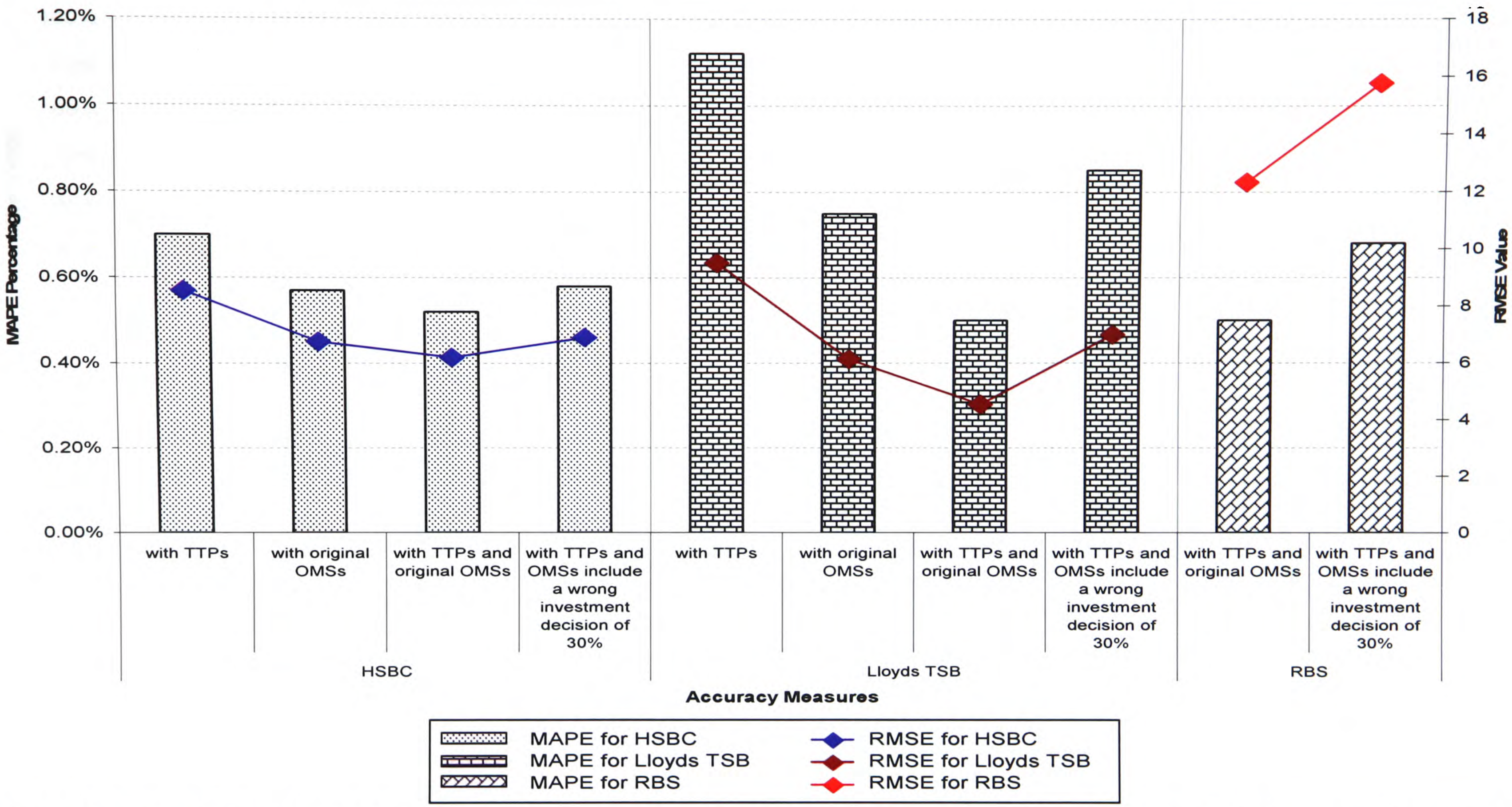

Figure 5.15: The RMSE and the MAPE of the forecasting models for HSBC, Lloyds TSB and RBS built using the *OMSs* including a wrong investment decision of 30%. The figure shows that the forecasting models, built using the daily *OMSs* including a wrong investment decision of 30%, produced comparable accuracy measures with the forecasting models built using the *TTPs*, the *OMSs* and both the *TTPs* and the *OMSs* together

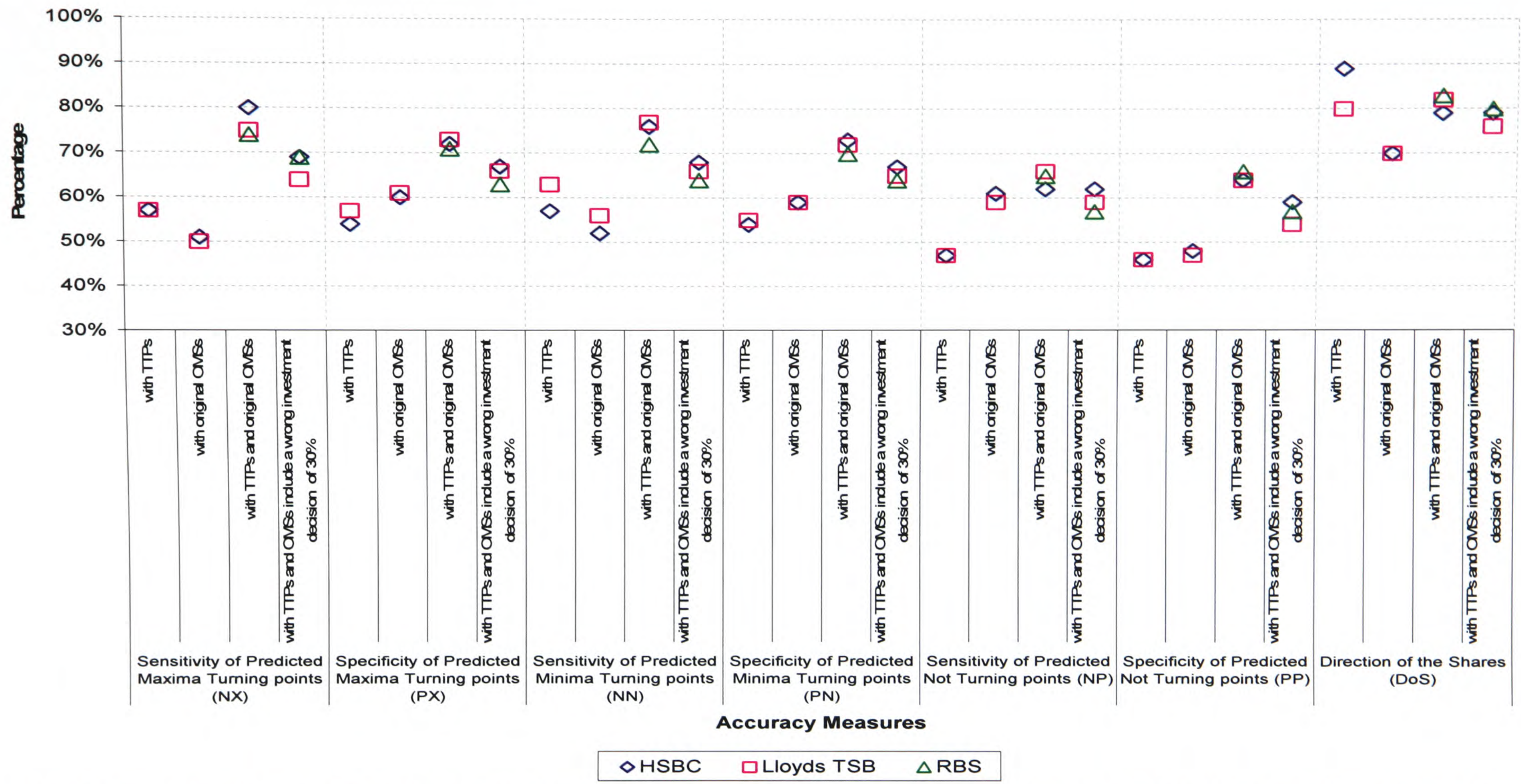

Figure 5.16: The sensitivity and specificity of predicted turning points (maxima, minima and 'not turning points') and the direction of the shares of the forecasting models for HSBC, Lloyds TSB and RBS built using the daily *OMSs* including a wrong investment decision of 30%. It can be seen that the forecasting models, built using the daily *OMSs* including a wrong investment decision of 30%, generally outperformed the forecasting models built using the *TTPs* and the *OMSs* separately

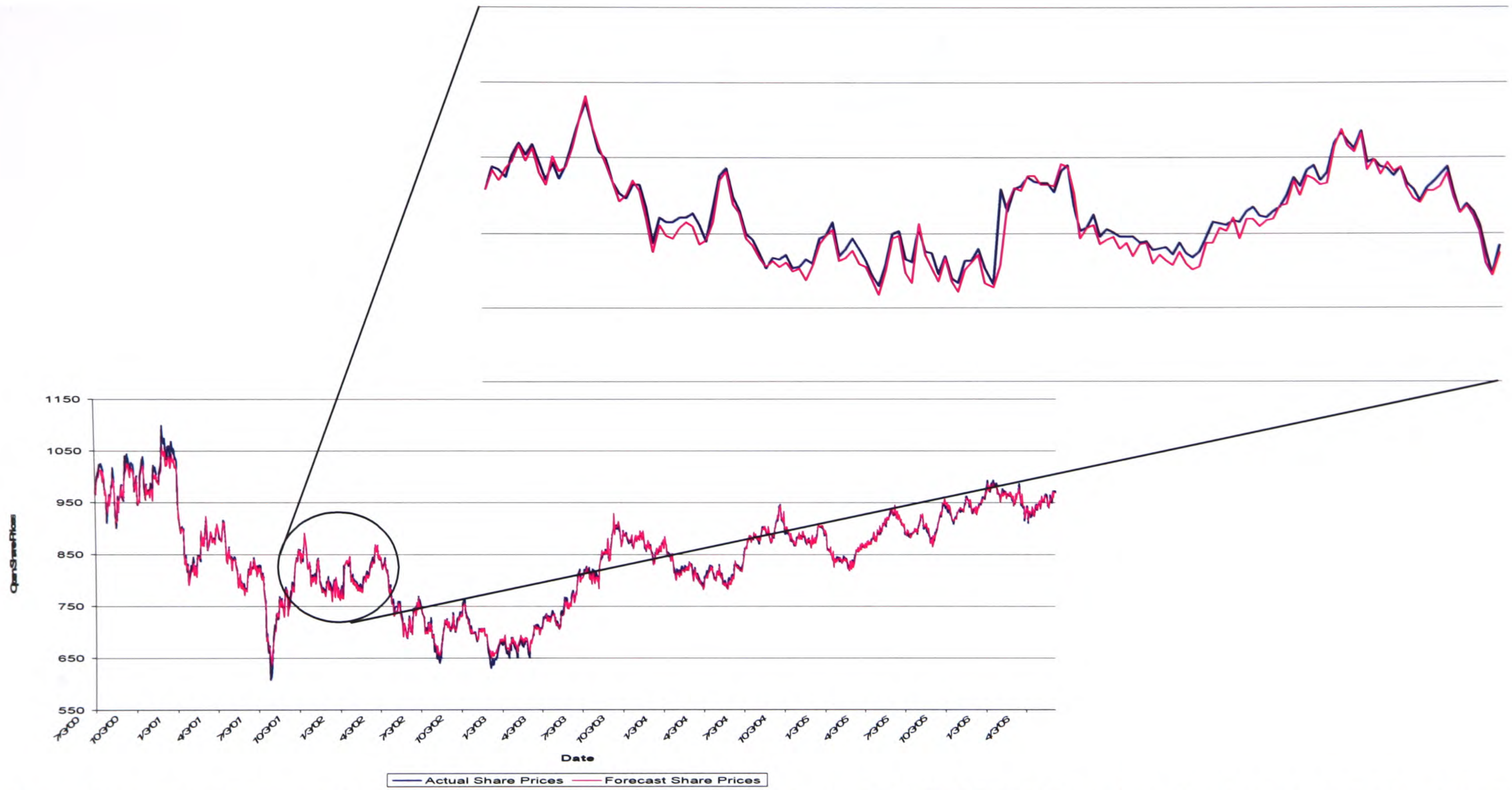

Figure 5.17: Actual and forecast daily open share prices of the concluding forecasting model for HSBC. This figure shows that there are small vertical lags in certain places between the actual and the forecast values

Figure 5.18: Actual and forecast daily open share prices of the concluding forecasting model for Lloyds TSB. It can be seen that there are small vertical lags in certain places between the actual and the forecast values

Figure 5.19: Actual and forecast daily open share prices of the concluding forecasting model for RBS. Small vertical lags in certain places, can be seen in this figure, between the actual and the forecast values

CHAPTER 6

RESULTS AND FINDINGS

6.1 Introduction

The results of modelling the case study datasets using RW, GARCH and the BPNN approaches were introduced in Chapter 5. The aim of these modelling experiments was to evaluate the developed framework (i.e. forecasting algorithm, input data and the accuracy measure) in modelling the share prices of the case studies from the banking sector and, thereafter, producing one step-ahead forecasts.

In this chapter, Section 6.2 introduces a comparative analysis of the experimental modelling. Section 6.3 introduces the forecasting results of the concluding forecasting models of each bank. Section 6.4 discusses the findings of this research. Further verifications of the findings were investigated using a new time series of the historic open share prices of Barclays Bank, are introduced in Section 6.5.

6.2 Comparative Analysis

This section presents a comparative analysis of the experimental modelling of the case study share prices, introduced in the Chapter 5, obtained using three different forecasting approaches, namely the Random Walk (RW), GARCH and the BPNN. Although the performances of these techniques in modelling the case study datasets are compared in this section, the general benchmark forecast accuracy values, established by Gately (1996) for financial forecasting, are mainly utilised in the comparison analysis carried out in this section.

As introduced in Section 5.2, the values of the accuracy measures obtained from modelling the share prices using the established benchmark models, shown in Table 5.1, were 0.30%, 31%, 31%, 48%, 42%, 43%, 30% and 49% for the MAPE, NX, NN, NP, PX, PN, PP and DoS respectively.

In the following sections, these values are compared with the accuracy measure values obtained from modelling the case study time series using the RW, GARCH and the BPNN.

6.2.1 Random Walk Model

The time series modelling using the RW model for HSBC, Lloyds TSB and the RBS, produced inferior models in terms of the accuracy measures above compared to the established benchmark model (introduced in Section 5.2), as shown in Figures 6.1.

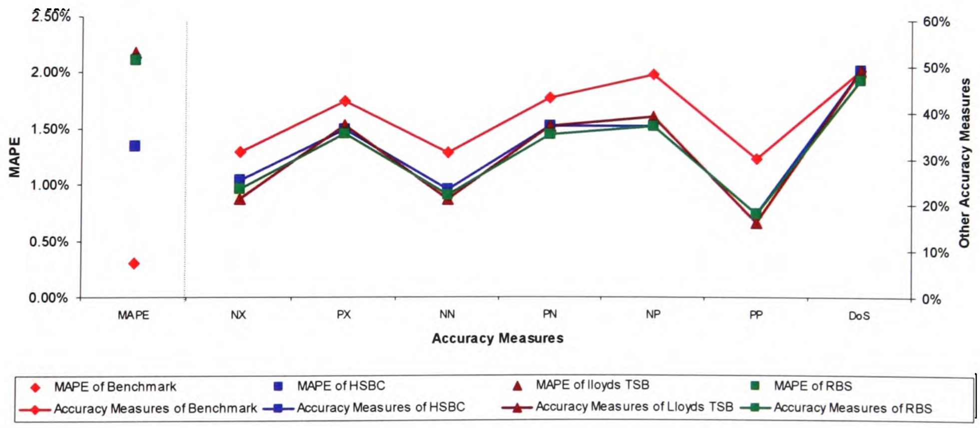

Figure 6.1: The accuracy measures of the HSBC, Lloyds TSB and RBS forecasting models, built using the RW model, compared to the benchmark model. It can be seen that the RW model generally produced unacceptable accuracy measures compared to established benchmark model

It can be seen from Figure 6.1 that the RW model failed to surpass the benchmark model in terms of the MAPE measure as relatively excessive MAPE values were produced for HSBC, Lloyds TSB and the RBS using the RW model compared to the established benchmark model. In addition, the NX, NN, NP, PX, PN and PP were lower than those obtained using the established benchmark model. Furthermore, the DoS was the only measurement which was found to be comparable for the RW approach and the established benchmark values.

In conclusion, the RW model did not achieve an adequate forecasting model for the share prices from the banking sector. For that reason, it is evidence to suggest that the share prices of HSBC, Lloyds TSB and the RBS follow a non-random movement.

6.2.2 *GARCH Model*

As introduced in Section 5.2.3, the GARCH approach failed to produce adequate forecasting models for Lloyds TSB and the RBS. Therefore, based on the investigation of the time series considered in this research, the application of the GARCH approach is limited in terms of the data series examined. However, for HSBC, the forecast accuracy measures resulting from GARCH model and these from the established benchmark and RW models are shown in Figure 6.2.

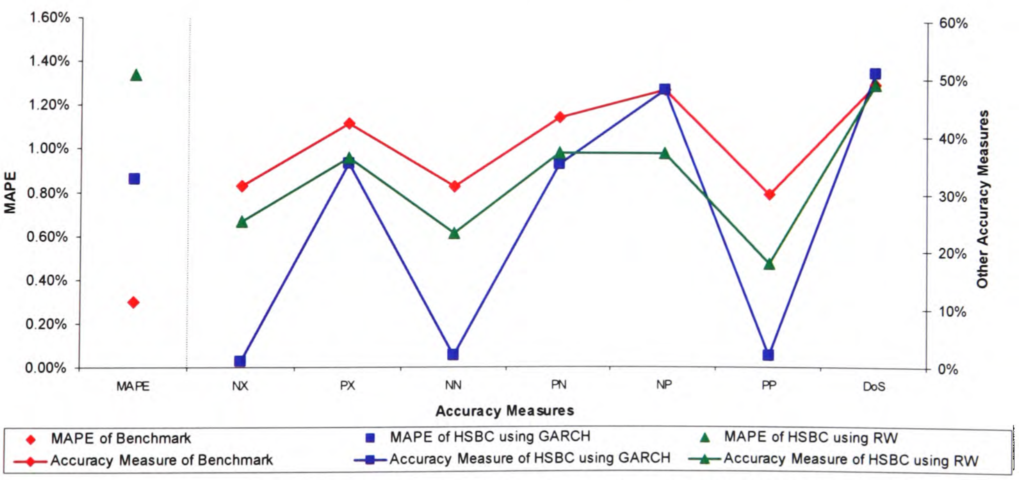

Figure 6.2: The accuracy measures of HSBC data using the GARCH, the established benchmark and RW models. This figure shows that the HSBC forecasting model using GARCH generally underperforms compared to the established benchmark and RW models

It can be seen from Figure 6.2 that the GARCH model was inferior to the established benchmark model and is comparable to the RW model in terms of the MAPE. In addition, the NX, NN and PP of the GARCH model were relatively low compared to the established benchmark and RW models. However, the GARCH model is comparable to the established benchmark and the RW models in terms of the NP, PX, PN and DoS.

Furthermore, although the ACF and PACF of the GARCH residuals (shown in Figure 5.7) of the HSBC forecasting model show no evidence of patterns remaining in the data, Figure 5.8 shows that the model provides persistent lag of one day in the forecast values. Therefore, although the ACF and PACF suggest that any existing patterns were captured by model, it has generally failed to yield an adequate model.

Conclusively, the forecast accuracy measures obtained from the concluding forecasting models built using RW and GARCH models were scheduled to be used as benchmarks in this research, in addition to the forecast accuracy measures obtained from the established model. These forecast accuracy measures show that their corresponding models were overall not sufficient to produce reliable forecasts for the share prices of the case studies. Therefore, the BPNN was considered to model and forecast the share prices of the banking sector.

The following section introduces a comparison between the concluding forecasting models built using the BPNN and the other forecasting models investigated in this research.

6.2.3 Back-propagation Neural Network (BPNN)

BPNN was used in this research to model and forecast the daily share prices of the case studies.

A concluding forecasting model of each bank, introduced in Section 5.3.5 for HSBC, Lloyds TSB and RBS, was initially compared with the established model since it was observed to surpass the RW and GARCH models, as explored above. Figure 6.3 gives the forecast accuracy measures of the neural network and established benchmark model. It can be seen from the figure that, although the MAPE of the constructed model is higher than the MAPE of the established benchmark errors, the forecast accuracy measures of the neural network models were superior in terms of the NX, NN, NP, PX, PN, PP and DoS.

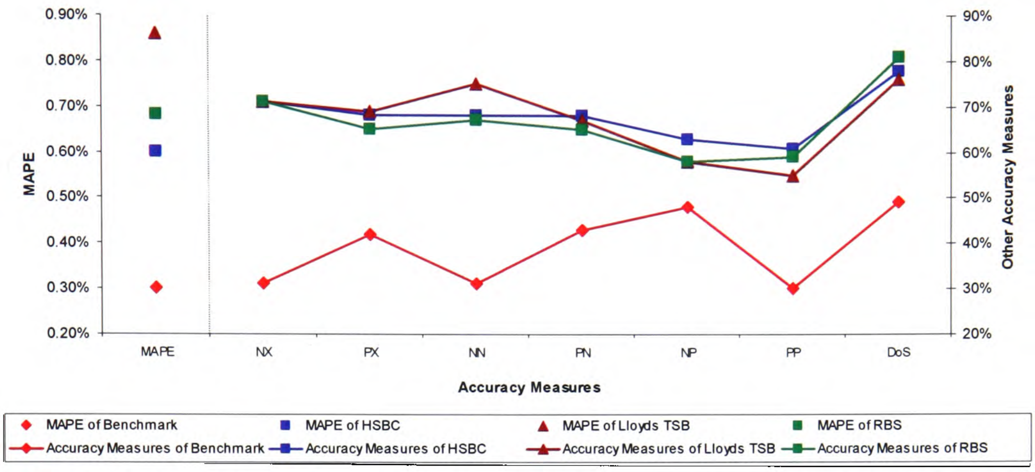

Figure 6.3: The accuracy measures of the HSBC, Lloyds TSB and RBS forecasting models built using the BPNN and the established benchmark model. It can be seen that forecasting models built using the BPNN generally outperform the established benchmark

The superiority of these models is realised through the use of, as explained in Section 3.2, the novel technical indicators representing the market knowledge. Hence, the concluding forecasting models of HSBC, Lloyds TSB and the RBS were generally superior to the established benchmark model in terms of the forecast accuracy measures NX, NN, NP, PX, PN, PP and DoS which were considered in this research to be the most influential accuracy measures used to evaluate the financial forecasting models.

It can also be noted that, in comparison with the RW and GARCH approaches, the Back-propagation approach outperforms the obtained forecasting models in terms of the most significant accuracy measures in financial applications argued in this research. Therefore, this finding adds to the mounting evidence that the BPNN is a superior approach in modelling the share prices from the banking sector.

The concluding forecasting models of each bank obtained using the BPNN were used to produce genuine one step-ahead out of sample forecasts for the share prices for the case study datasets. These forecasts are presented next.

6.3 Forecasting Results

Following the construction of adequate neural network forecasting models for each of HSBC, Lloyds TSB and RBS (as introduced in the Chapter 5) these models were employed to produce one step-ahead forecasts of the open share prices of each bank for a period of five days ahead (i.e. from 2nd April to 6th April 2007). These forecasts represent genuine out of sample forecasts for these models and are produced as a final model evaluation stage. Therefore, the historic data, ranging from 3rd July 2000 to 30th March 2007, was used as input to the models to forecast the share prices for the following day, i.e. 2nd April 2007. Thereafter, the observed value of this day was added to the input dataset which was to predict the following day, and so on until forecasts for the share price on 6th April 2007 was obtained.

Five days ahead are a short period to evaluate the forecast accuracy of the models, but it is adopted in this research as it is very difficult for research purposes to get the expert opinion, which is required to set up the values of the TTP_t and the OMS_t, for more than five days for each time series used in this research.

However, as previously mentioned, the forecasting process requires generating the TTP_t and the OMS_t, which represent the market knowledge, of the last day of the series. Hence, forecasting the future open share prices was carried out firstly without including market knowledge in the model. Then, real-life market knowledge was used to generate the TTP_t and the OMS_t in the last day of the used data, at time t, hence forecasts that include market knowledge were produced.

The two sets of forecasts and their comparisons are introduced in turn below.

6.3.1 Models that Exclude Market Knowledge Variables

The forecasts of the future share prices of the case studies, shown in Figures 6.4, 6.5 and 6.6 for HSBC, Lloyds TSB and RBS respectively was carried out with no market information assumed available, but through artificially generating the TTP_t and the OMS_t of the last day of the used input data. This was done by, for the TTP_t, simulating the expert's opinion to be used as input when forecasting the future share prices. More specifically, the simulated turning points generated using the trinomial distribution (+1, 0 and -1) with parameters based on the observed percentage of the turning points in the historic data, as shown in Table 6.1 below. Whilst for the OMS_t, the value 0 was used as the OMS_t in the last day of the used input data.

Dates	Banks		
	HSBC	Lloyds TSB	RBS
30th March 2007	+1	0	1
2nd April 2007	0	-1	-1
3rd April 2007	1	0	0
4th April 2007	-1	0	0
5th April 2007	0	0	-1

Table 6.1: the simulated turning points of the three banks, used trinomial distribution with parameters based on the observed percentage of the turning points, to forecast the future share prices for the period from 2nd April 2007 till 6th April 2007

Subsequently, the generated turning point, TTP_t, and the 0 value of the OMS_t were added to the available data to forecast the next day's share price.

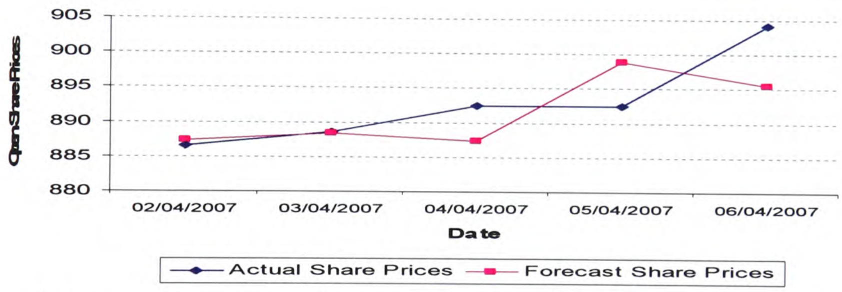

Figure 6.4: Actual and out of sample forecast for the daily open share prices for HSBC of the first week of April 2007 obtained form model with no market knowledge variables. The graph shows that the direction of the share was correctly predicted in 25% of the paints

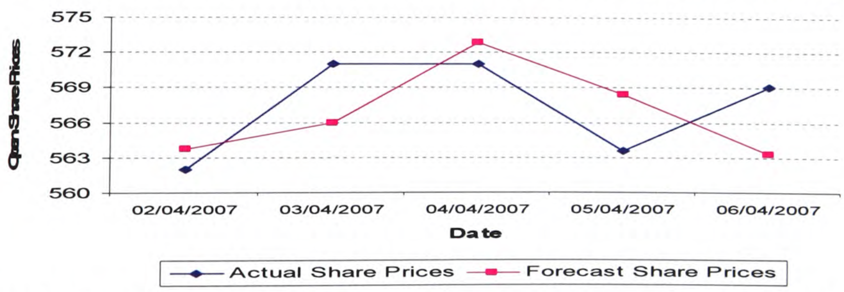

Figure 6.5: Actual and out of sample forecast for the daily open share prices for Lloyds TSB of the first week of April 2007 obtained form model with no market knowledge variables. The graph shows that the direction of the share was correctly predicted in 50% of the paints

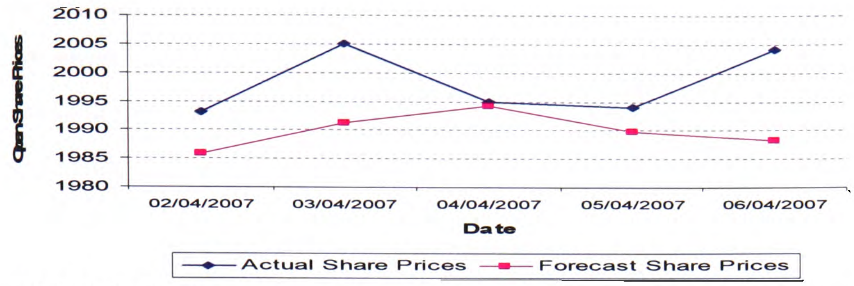

Figure 6.6: Actual and out of sample forecast for the daily open share prices for RBS of the first week of April 2007 obtained form model with no market knowledge variables. The graph shows that the direction of the share was correctly predicted in 50% of the paints

It can be seen from Figures 6.4, 6.5 and 6.6 for HSBC, Lloyds TSB and RBS that the forecasts reproduced the direction of the shares in 25%, 50% and 50% of cases with a MAPE of 0.47% 0.67%, and 0.42% for HSBC and Lloyds TSB respectively.

In conclusion, the one step-ahead forecasting models that included simulated market knowledge as input have produced acceptable forecasts in terms of the MAPE, while in terms of the DoS, these forecasts were unreliable compared to DoS values obtained from the training models.

Therefore, given the results above, market information data was added to the models as input, in the last day of the used data, to forecast the future share prices of the banking sector. This is introduced in the following section.

6.3.2 Models that Include Market Knowledge Variables

Ideally, the forecasting models need to employ market knowledge as an input to predict whether there will be a turning point or not, TTP_t, and the intensity of the change in the prices of the shares, as measured by the novel OMS_t, in the last day of input data, so as to improve the share price forecasts accuracy.

In this research, the TTP_t was determined as given in Table 3.2 when market information is available, and, otherwise, was simulated, as introduced in Section 6.3.1, when there was no market information available. Whilst the OMS_t was determined as given in Table 3.1 when there is market information or, otherwise, a value of 0 was used when there was no market information available.

It is worth noting that evaluating the factors below to decide where the market was going to move was carried out by a financial expert who is a member of the supervision team in this research, to determine the effectiveness of this factor on the market and, subsequently the values of TTP_t and OMS_t at time t. Section 6.3.2.1 introduces typical examples of how market knowledge may be used in determining the TTP_t and the OMS_t at time t.

6.3.2.1 Market Knowledge Evaluation for HSBC

On 30th March 2007, HSBC Bank announced that a retail banking network will be established in Japan at the beginning of 2008 with an expectation of opening up to 50 new branches over the next four years. On the same day, Stephen Green, group chairman of HSBC Holdings Plc., said that the HSBC Bank was in the same situation as the troubled mortgage businesses in USA and this may continue for three years (http://www.digitallook.com).

The first announcement was likely to affect the share price of the next trading day positively while the second was likely to result in a decrease of the share prices. Therefore, the collective influence of the two events was that the share price of HSBC on 2nd April 2007 had a weak negative effect. Hence, the TTP_t on 30th March 2007set to (+1), as the share price on the 29th March (y_{t-1}) was going up and the expected share price on 2nd April 2007 (y_{t+1}) would come down. The OMS_t at time t is (-1) to measure the movement intensity of these events.

An inspection of the data showed that the forecast share prices on 2nd April 2007, obtained using the concluding model, came down on the previous trading day, as shown in Table 6.2 below.

Date	Actual Share Price	Forecast Share Price
30th March 2007	888.00	
2nd April 2007	886.50 ↓	**880.76** ↓

Table 6.2: Actual and out-of-sample forecast for the HSBC open share prices on the 2nd April 2007 obtained using the market knowledge

In the following trading day (i.e. on the 2nd April 2007), HSBC was one of four foreign banks to start their operations in China employing more than 3000 staff in 14 main branches and 21 other sub-branches (http://www.digitallook.com). In this case, the share price in the following trading day was likely to go up as that will possibly affect the general performance of HSBC in the future. The share price on 2nd April was coming down and it was expected that the share price on 3rd April would go up, therefore, the TTP_t was set to (-1) indicating a change in the direction of the shares, while the OMS_t was set to (+1).

The forecast for the 3rd April 2007, introduced in Table 6.3, was an increase in the share prices compared to the actual value in the previous trading day as a result of these values of the TTP_t and the OMS_t above.

Date	Actual Share Price	Forecast Share Price
2nd April 2007	886.50	
3rd April 2007	888.50 ↑	**888.34** ↑

Table 6.3: Actual and out-of-sample forecast for the HSBC open share prices on the 3rd April 2007 obtained using the market knowledge

Another typical example of the use of market knowledge in setting the TTP_t and OMS_t is when it was reported that the president and CEO of HSBC Bank in China, Richard Yorke, informed the shareholders on 3rd April 2007 that the growth plan was restricted due to the limited experience of their staff at the time (http://uk.finance.yahoo.com). This strategy had a weak positive effect on the share prices of the next trading day. This is because it was also announced that 1000 more staff would be recruited to improve the current experience level of the staff.

The share price on 3rd April was going up and it was expected that the share price on the 4th April would continue to go up. Therefore, there was no turning point set for the last day of the used data, i.e. a value of TTP_t equals (0) was used, while the OMS_t was set to (+1).

The result, presented in Table 6.4, shows that the forecast share price on 4th April 2007 has gone up, i.e. in the same direction of the actual share price.

Date	Actual Share Price	Forecast Share Price
3rd April 2007	888.50	
4th April 2007	892.50 ↑	**896.04** ↑

Table 6.4: Actual and out-of-sample forecast for the HSBC open share prices on the 4th April 2007 obtained using the market knowledge

On the 4th April 2007, there were no reported events in the market that can be used in setting the TTP_t and OMS_t of the input. Thus, the TTP_t and OMS_t were determined using the modus operandi of Section 6.3.1.

On the 5th April 2007, HSBC promoted a new mortgage deal available to the UK market. This promotion was to offer fee-free mortgages until 30th the April 2007 (http://www.digitallook.com). This instance had an average positive effect on the share prices of the next trading day, i.e. (+2) for the OMS_t and (0) for the TTP_t as the share price on 5th April followed the same directions of the previous trading day and the expected movement of the share on 6th April was on the rise.

The forecast price on 6th April 2007, using the process above, was in the same direction of the actual share price, as shown in Table 6.5 below.

Date	Actual Share Price	Forecast Share Price
5th April 2007	892.50	
6th April 2007	904.00 ↑	**907.59** ↑

Table 6.5: Actual and out-of-sample forecast for the HSBC open share prices on the 6th April 2007 obtained using the market knowledge

6.3.2.2 Examples of Using the Market Knowledge for Lloyds TSB

On 30th March 2007, Lloyds TSB Group Plc. announced that the capital was increased by 506311 ordinary shares, of £0.25 per share, since 28th February 2007 (http://www.mediacentre.lloydstsb.com). This announcement was likely to affect the share price of the next trading day positively in a weak intensity. Therefore, the TTP_t is (0) indicating no change in the direction of the shares and the OMS_t is (+1).

The forecast result, obtained by using the TTP_t and the OMS_t values set according to the above predictions, shows that the forecast share price on 2nd April 2007 followed the same direction of the actual share price, as shown in Table 6.6.

Date	Actual Share Price	Forecast Share Price
30th March 2007	559.50	
2nd April 2007	562.00 ↑	**562.89** ↑

Table 6.6: Actual and out-of-sample forecast for the Lloyds TSB open share prices on the 2nd April 2007 obtained using the market knowledge

In the following trading day, no salient market events were reported, hence there was no information to be used to determine the TTP_t and the OMS_t. Therefore, the TTP_t and OMS_t were determined as introduced in Section 6.3.1.

On 3rd April 2007, Lloyds TSB launched a business account consistent with Islamic Shariah to allow the Muslim businesses in UK to deal with the bank in terms that are compatible with their faith (http://www.mediacentre.lloydstsb.com). This was likely to drive the share price on 4th April 2007 up and in this case, no change in the direction of the shares was expected to occur. Therefore, the values of TTP_t and OMS_t were set to (0) and (+1).

The forecast obtained using these values predicted an increase in the share price on 4th April 2007, but the actual share price remained the same as the share price of the previous trading day with no change.

Date	Actual Share Price	Forecast Share Price
3rd April 2007	571.00	
4th April 2007	571.00 ⇆	**574.16** ↑

Table 6.7: Actual and out-of-sample forecast for the Lloyds TSB open share prices on the 4th April 2007 obtained using the market knowledge

On 4th April 2007, there was no salient market information was to be used to set the values of TTP_t and OMS_t in forecasting the share price of the following trading day. Therefore, the market knowledge inputs on this day were determined in the same way of Section 6.3.1.

On the 5th April 2007, Lloyds TSB announced that it will introduce a new service, to travellers, namely a travel card. This card, which is not linked to the bank account, is a pre-paid card that can be used in shops and to withdraw cash from ATMs (http://www.mediacentre.lloydstsb.com). This initiative was expected to raise the share price of the next trading day with an average intensity. Therefore, the TTP_t has set to (0), and the OMS_t to (+2).

Table 6.8 shows the forecast share price on 6th April 2007 obtained using the process above, which was in the same direction of the actual share price.

Date	Actual Share Price	Forecast Share Price
5th April 2007	563.50	
6th April 2007	569.00 ↑	**572.82** ↑

Table 6.8: Actual and out-of-sample forecast for the Lloyds TSB open share prices on the 6th April 2007 obtained using the market knowledge

6.3.2.3 Examples of Using the Market Knowledge for RBS

Apart from 3rd April 2007, it was not possible to determine significant market information can be used in setting the values of TTP_t and OMS_t for the shares of the RBS. Therefore, the TTP_t and the OMS_t in each day were determined similarly to Section 6.3.1.

On the 3rd April 2007, the RBS Group Plc. announced the sale of the Royal Bank of Scotland International (Holdings) Limited, an owned subsidiary of RBS and BNY International Financing Corporation, to the BNP Paribas S.A (http://uk.finance.yahoo.com). This transaction had a negative effect on the share price of the next trading day on average in terms of the intensity. Therefore, the TTP_t was (+1) indicating a change in the direction of the shares, and the OMS_t was (-2).

The forecast share price on the 4th April 2007, as presented in Table 6.9 below, followed the same direction of the actual share price compared to the value in the previous trading day.

Date	Actual Share Price	Forecast Share Price
3rd April 2007	2005.00	
4th April 2007	1995.00 ↓	**1986.27** ↓

Table 6.9: Actual and out-of-sample forecast for the RBS open share prices on the 4th April 2007 obtained using the market knowledge

It is worth noting that the forecasting process of the open share prices for one step-ahead has to be carried out early enough to buy or sell the shares and before the market closes as otherwise any price movement will already have taken place when the market opens in the next trading day.

6.4 Discussion of Findings

Developing and calibrating a framework that can be used to model and forecast the share prices was the essential aim of this research. Therefore, innovative approaches were investigated and developed in order to achieve this aim. These were the following:

1. Development of a novel forecasting algorithm that can be applied in modelling and forecasting the share prices in the banking sector.
2. Two novel technical indicators, representing the market knowledge, were developed to be used as inputs in building the forecasting model of the share prices.
3. Employing the market knowledge, reflecting the financial experts' opinion, as input, at time t, to improve the share price forecast of the next trading day.
4. Development of an accuracy measure, namely the correctly identified turning points, to be used to evaluate the performance of the financial forecasting models.

In the remainder of this section, each of the four developments above will be discussed in detail.

6.4.1 The Novel Forecasting Algorithm

A development of an algorithm that can be used in modelling and forecasting the financial time series, as introduced in Section 4.7, was investigated in this research since there is no standard forecasting procedure or technique that can be used in modelling and forecasting the financial time series. The proposed novel algorithm consists of six steps with feed-back and feed-forward mechanisms.

These feed-back and feed-forward mechanisms helped improve the modelling of the case study datasets, investigated in this research, since these mechanisms are used to update the following:

1. The pre-processed data when insufficient forecasting model was obtained from training and testing steps (evaluated in terms of the forecasting accuracy measures).

2. The prior information when obtaining unacceptable forecasts value which is evaluated, as a rule of this research, in terms of the expected movement made by the financial experts.

3. The prior information after each adequate forecasting model obtained in order to develop the forecasting model for financial application. This is because there is no guarantee that the adequate forecasting model built is suitable for the future.

In addition to the feed-back and feed-forward mechanisms, two novel stages (the Prior Information and the Reduction to Parsimonious Form) were included to the novel algorithm so as to introduce the forecasting practicality of the investigated time series. The Prior Information stage allows investigating the contemporary forecasting tools and/or techniques, while the Reduction to Parsimonious Form stage allows for a less complex model to emerge, thus facilitating the overall insertion of inputs. Thus, the selection of both adequate forecasting techniques and of a less complex model is necessary in the evaluation of the overall feasibility of the obtained models.

In general, it is believed that this algorithm superiorly ameliorates the modelling of financial time series and, hence, produces improved forecast values. In this research, the empirical results show that superior forecasting models were obtained by applying the proposed algorithm compared to the financial forecasting models published in the finance literature.

6.4.2 The Novel Technical Indicators

This research developed two technical indicators that are salient to the financial time series and hence can inform and improve the reliability of modelling and forecasting the share prices from the banking sector. These novel technical indicators, which can be seen as representing the market knowledge, were the Turning Points (*TPs*) and the Ordinal Market Sentiments (*OMSs*) technical indicators. These variables were used as inputs when modelling the share prices from the banking sector using an adaptive BPNN.

The *TPs* technical indicator variable was developed to identify local points whereby a change in the direction of the share price time series is observed which, when used as an input, considerably improved the financial forecasting models. The implementation of the *TPs* yielded a significant increase in the sensitivity and specificity of predicted turning points in within-sample forecasts, and hence, led to a more reliable identification of local changes in the direction of the shares. More specifically, in the course of this research, the Binary Turning Points (*BTPs*) and Type of Turning Points (*TTPs*) were investigated as inputs in building the forecasting model. The modelling results show that the *TTPs* further improved the forecasting models obtained using the *BTPs* as input in terms of all the accuracy measures employed in this research. Therefore, the *TTPs* technical indicator was adopted in this research instead of the *BTPs*.

The *OMSs* technical indicator variable was developed to measure the directional intensity in the share prices behaviour. The forecasting models built using the *OMSs* as input were generally superior compared to the forecasting models built using the *TTPs* and those built without market knowledge.

Lower frequency domains of the *OMSs* (i.e. weekly, bi-weekly and monthly *OMSs*) were investigated as input instead of the daily *OMSs*, so as to provide the modelling process with a smooth movement of the *OMSs*. This may help uncover further patterns in the share prices, and help reduce the high-cost of the consultancies and the expert's opinion.

However, using the lower frequencies of the *OMSs* as inputs in building the forecasting models produced inferior accuracy measures compared to the accuracy measures of the models built using the daily *OMSs*. This is because the daily *OMSs* corresponds to the data used in this research which is the daily historic share prices. In spite of this, the forecasting models built using the lower frequencies of the *OMSs* for HSBC, Lloyds TSB and RBS generally outperformed the established benchmark model in terms of the NX, NN, NP, PX, PN, PP and DoS, as shown in Figure 6.7, 6.8 and 6.9 for the accuracy measures obtained from the models built using weekly, bi-weekly and monthly *OMSs*. Therefore, these inputs are supposed to be usable to build acceptable forecasting models. However, with the aim of further improvement for the forecasting models in this research, the daily *OMSs* technical indicator was adopted.

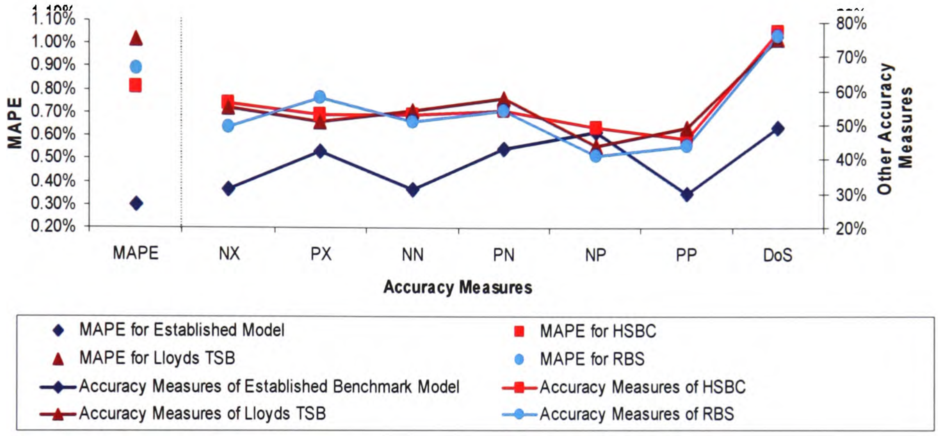

Figure 6.7: The accuracy measures of the HSBC, Lloyds TSB and RBS BPNN forecasting models built using the weekly *OMSs* compared to the accuracy measures of the established benchmark model. It can be seen from this figure that the forecasting models built using the BPNN generally outperformed the established benchmark model

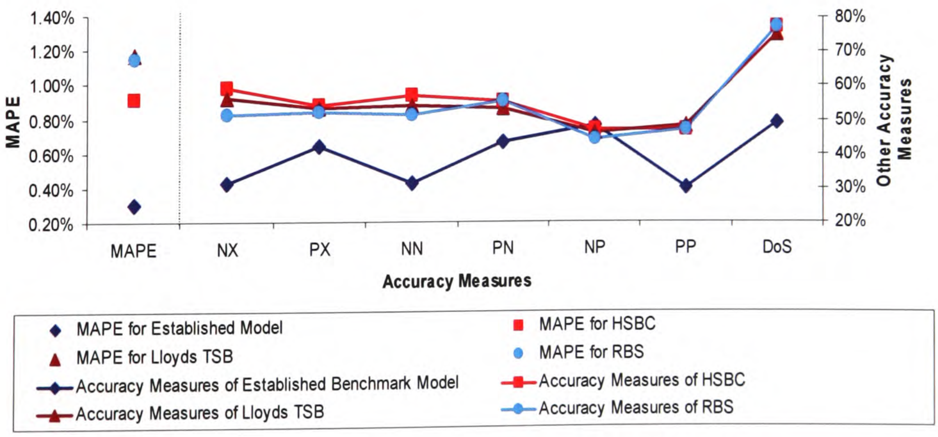

Figure 6.8: The accuracy measures of the HSBC, Lloyds TSB and RBS BPNN forecasting models built using bi-weekly *OMSs* compared to the accuracy measures of the established benchmark model. It can be seen that the forecasting models built using the BPNN generally outperformed the established benchmark model

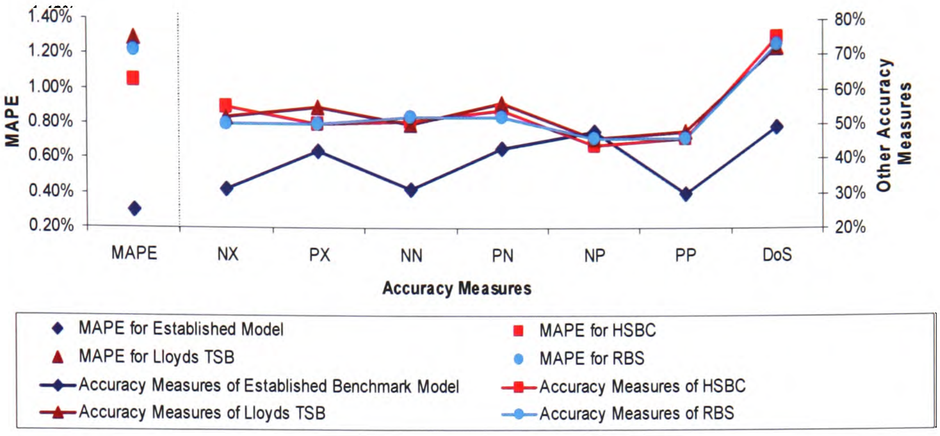

Figure 6.9: The accuracy measures of the HSBC, Lloyds TSB and RBS BPNN forecasting models built using monthly *OMSs* compared to the accuracy measures of the established benchmark model. It can be seen that the forecasting models built using the BPNN generally outperformed the established benchmark model

Since the *TTPs* and the *OMSs* when used separately as inputs in modelling the share prices improved the forecast accuracy measures of the forecasting models, the *TTPs* and *OMSs* were employed together as inputs when building the forecasting models and, hence, that led to further improvements in all the accuracy measures utilised in this research.

Conversely, since a mistake in investment decision-making can occur, an uncertain component was included in the daily *OMSs* when used as an input in order to simulate the uncertainty in the expert's opinion about the state of the market. This uncertain component, which was generated using the normal distribution with mean μ=0 and standard deviation σ=0.5, was added to the original *OMSs*, so as to simulate a change in the movement intensity of the *OMSs* by 30% which was believed to best reflect the veracity of daily forecasting in the banking sector.

As a result, using the *OMSs*, whilst including a wrong investment decision of 30%, produced acceptable forecasts compared to the best forecasting models obtained using the *TTPs* and the original *OMSs* (i.e. no wrong investment decision) separately. Furthermore, this new modelling was generally comparable with the best forecasting models built using both the *TTPs* and the original *OMSs* together. Hence, it is expected that this would be useful in building an acceptable forecasting model when any wrong decision occurred within 30%.

In conclusion, the *TTPs* and the *OMSs* considerably improved the modelling and forecasting the share prices in the banking sector and it is expected that these technical indicators would be significant inputs in any financial forecasting application.

6.4.3 Measuring Market Knowledge

Since the stock prices in the market are affected by a large number of the factors, a method was developed in this research to use these factors (i.e. the market knowledge) as an input in modelling share prices. This market knowledge, which reflects the expert opinion, was obtained through collecting and studying the market information available through the media in order to set the *TTPs* and the *OMSs* at time *t*, as introduced in Section 3.2.

As introduced in Section 6.3, forecasting the share prices without using the market knowledge in setting the *TTPs* and the *OMSs* at time *t* produced unreliable forecasts in terms of the direction of the shares in the majority of the cases. Conversely, the forecasts of the share prices produced using the market knowledge, which usually represents the market information published in the media, in obtaining the TTP_t and the OMS_t, were found to generally move in the same direction of the actual share prices at time *t*.

Therefore, using the market knowledge greatly improved the forecast-ability of the share prices from the banking sector.

6.4.4 Accuracy Measure

Due to the nature of the application presented in this research, the utilisation of the turning points (*TPs*), which is a point beyond which the direction of the time series changes, as an accuracy measure was valuable in the selection of an adequate forecasting model. Therefore, a novel application of the accuracy measure, namely the Correctly Identified Turning Points (turning points denoted by *1* and 'not turning points' denoted by *0*), was conducted in this research to evaluate the performance of the financial forecasting models.

Moreover, this accuracy measure was further developed to include the type of turning points, namely maxima turning points (+1), minima turning points (-1) and 'not turning points' (0), so as to provide more detailed evaluation of the forecasts and, hence, provide a further aid in the model selection process.

Although obtaining high percentages of all types of the sensitivity and specificity of predicted turning points measure implies that an adequate forecasting model has been built the sensitivity of predicted maxima and minima turning points (NX and NN respectively) are considered, in our opinion, more important than other types of the correctly identified turning points. This is because, obtaining high percentages of the NX and NN refers to the model achieving higher percentage of the correctly identified direction of the shares and, hence, represents the power of the forecasting model.

In conclusion, the novel selection process was improved in this research when the developed correctly identified turning points measure was used, as this measure provides a further understanding of the market's dynamics and fluctuations, and also relates the model's performance to the day-to-day dealing of shares. The direction of the shares measure, developed by Yao and Poh (1995), also had an important role in selecting an adequate forecasting model for the share prices in the banking sector.

With the intention of producing more evidence to evaluate the performance of the developed framework in modelling and forecasting share prices, the framework was used to model the share prices of Barclays Bank during exceptional circumstances. This application is introduced next.

6.5 Modelling Barclays Share Prices

Modelling the share prices of Barclays Bank, covering the period from 1st July 2002 until 12th September 2008 (Listed in Appendix C), was investigated in this research in order to further evaluate the research's findings.

The period form 1st July 2002 until 31st December 2007 was used to train the model and the rest of that data was used to test the model. The modelling process followed the steps of the proposed algorithm. A concluding forecasting model was achieved which consists of 12 inputs (y_{t-4}, y_{t-3}, y_{t-2}, y_{t-1}, y_t, 5MA, 10MA, 20MA, 40MA, ∇y_t, *TTPs* and *OMSs* included a wrong investment decision of 30%) with 12 neurons in one hidden layer. This concluding model yielded within sample one step-ahead forecast accuracy measure that were comparable to the concluding forecasting models of HSBC, Lloyds TSB and RBS, as shown in Figures 6.10. These accuracy measures were 0.81%, 69%, 61%, 68%, 65%, 59%, 54% and 76% for MAPE, NX, NN, NP, PX, PN, PP and DoS respectively.

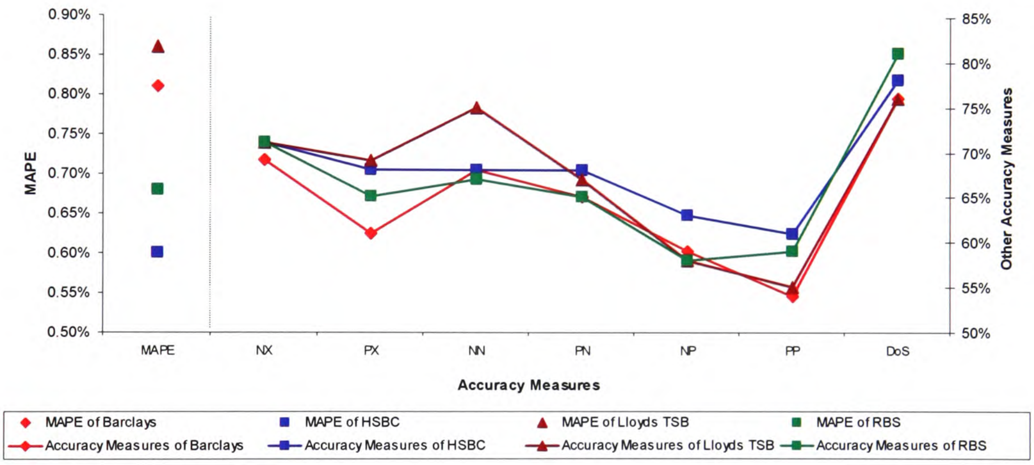

Figure 6.10: The accuracy measures of the concluding models of Barclays Bank, built using the BPNN, compared to the concluding models of HSBC, Lloyds TSB and RBS. It can be seen that the forecasting model of Barclays Bank generally comparable to the concluding models of HSBC, Lloyds TSB and RBS

Thereafter, testing the concluding model was performed using the period from 1st January 2008 till 12th September 2008, and the model yielded acceptable accuracy measures of 0.77%, 62%, 59%, 62%, 57%, 55%, 49% and 72% for MAPE, NX, NN, NP, PX, PN, PP and DoS, respectively. Therefore, this concluding forecasting model was considered to be acceptable and was used to produce genuine out of sample one step-ahead forecasts for the share prices of Barclays Bank.

The results above gave additional evidence to suggest that the developed technical indicators, the *TTPs* and *OMSs*, can improve the forecast accuracy of modelling the share prices from the banking sector in terms of sensitivity and specificity of predicted turning points (NX, NN, NP, PX, PN and PP), and the direction of the shares (DoS).

Subsequently, forecasting the share prices for one step-ahead using the concluding forecasting model was carried out using the market information to determine the *TTPs* and the *OMSs* for the last trading day of the used data. Forecasts were performed for the trading day 15th, 16th, 17th, 18th and 19th of September 2008 with market knowledge variables, as introduced below.

On 14th September 2008, the plea to the US Treasury Secretary to rescue the Lehman Brothers Inc. from their financial difficulties worsened the market speculations of any possible recovery (http://www.digitallook.com). This was likely to affect the share prices of the banking sector negatively with a strong intensity. Therefore, the TTP_t was (0) indicating no change in the direction of the shares and the OMS_t was set to (-3).

In the following trading day (i.e. on 15th September 2008), Lehman Brothers collapsed, having a negative effect on the share prices of the banking sector with a strong intensity. Therefore, the TTP_t was set to (0) indicating no change in the direction of the shares and the OMS_t was set to (-3).

On the 16th September 2008, Barclays agreed to buy certain parts of Lehman Brothers' failed business and was speculated to consider the further acquisition of other Lehman Brothers assets on "attractive terms" (http://uk.finance.yahoo.com). Therefore, and OMS_t was set to (+3) and the TTP_t was set to (-1) as the share price on 16th September was coming down and the expected movement of the share on 17th September was on the rise.

On 17th September 2008, the possible takeover of HBOS shares by Lloyds TSB caused insecurity in the market. Risk assessment reports predicted that around 1,000 HBOS branches would be closed down. Therefore, OMS_t was set to (-2) and the TTP_t was set to (+1) as the share price on 17th September was going up and the expected movement of the share on 18th September was to decrease.

Another typical example of the use of market knowledge in setting the TTP_t and OMS_t is when Barclays Bank placed new shares of £750m on 18th September 2008 in order to buy the core assets Lehman Brothers after the agreement of the UK Bank to buy the Lehman's North American investment banking and capital markets businesses (http://uk.finance.yahoo.com). This agreement meant that values of (+3) was set for the OMS_t and (-1) for the TTP_t as the share price on 18th September was coming down and the expected movement of the share on 19th September was on the rise.

As a result of using the values of TTP_t and OMS_t above, the forecast share prices of the 15th, 16th, 17th, 18th and 19th September 2008 (given in Table 6.10) were produced in the same direction of the actual share price. Figure 6.11 shows the actual and genuine out-of-sample forecast of the share prices of Barclays Bank.

Date	Actual Share Price	Forecast Share Price
12th September	343.00	
15th September	330.00 ↓	**335.30** ↓
16th September	302.00 ↓	**316.00** ↓
17th September	338.00 ↑	**329.50** ↑
18th September	315.00 ↓	**312.00** ↓
19th September	475.00 ↑	**338.25** ↑

Table 6.10: Actual and genuine out-of-sample forecast for the Barclays open share prices on the 15th, 16th, 17th, 18th and 19th September 2008 obtained using the market knowledge

Table 6.10 shows that all the forecast share prices of Barclays Bank were produced in the same direction of the actual share prices. Thus, an additional evidence of the success of using the market knowledge as input in forecasting the share prices of the banking sector was given in this section.

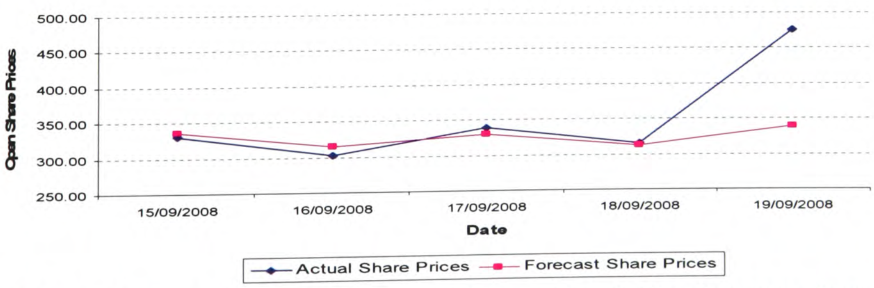

Figure 6.11: Actual and genuine out-of-sample forecast for the Barclays open share prices of the third week of September 2008 obtained using the market knowledge. It can be seen that the forecast share prices are in the same direction of the actual share prices

6.6 Chapter Summary

In this chapter, a comparative analysis of modelling the investigated share prices using Random Walk (RW), GARCH and the BPNN were discussed. The evidence suggests that the BPNN models outperformed those obtained using other forecasting approaches in terms of all the accuracy measures employed in this research.

The forecasting results of the concluding forecasting models of each bank using the models excluding and including the market knowledge as input which is used to set up the TTP_t and the OMS_t values in the last day of the used data were presented in this chapter. The evidence suggests that including the market knowledge produced reliable forecasts for the share prices of the banking sector.

The following section discussed the research's findings which was organised in four parts, each of which representing the findings that have been achieved in this research.

Finally, an additional time series, represented the open share prices of Barclays Bank covering the period from 1st July 2002 till 12th September 2008, was investigated in this chapter with the aim of presenting further evidence of the success of the findings, discussed in Section 6.4, in developing the modelling and forecasting the share prices from the banking sector. It showed that the developed framework would succeed in modelling and forecasting the share prices from the banking sector.

CHAPTER 7

CONCLUSIONS AND FUTURE WORK

This chapter provides a synopsis of how the research's objectives have been achieved with the main contributions to knowledge. Suggestions for future work are also provided.

7.1 Conclusions

Modelling and forecasting share prices are complicated processes due to the high volatilities in the share prices and in the financial markets. However, this research gives evidence to suggest that the share price time series can actually be modelled with acceptable reliability, to produce one step-ahead forecasts under normal market conditions. This was carried out by **1)** following the novel forecasting algorithm proposed in this research and **2)** using the two novel technical indicators, *TTPs* and *OMSs*, as inputs when building the forecasting models.

As case studies, the historic open share prices of HSBC, Lloyds TSB and the Royal Bank of Scotland (RBS) covering the period from 3rd July 2000 to 30th March 2007 were investigated and modelled to produce one step-ahead forecast for the share prices using the Random Walk (RW) model, GARCH model and BPNN.

The BPNN approach was used as a main approach in this research to model and forecast the share prices as it is an established approach in financial forecasting. In addition, the ability of this modelling approach to include a number of inputs is deemed more beneficial, and hence, possess the ability to model high volatility datasets compared to other established approaches. The other approaches which were therefore employed to provide benchmarks to evaluate the performance of the forecasting models obtained using the BPNN.

As observed, the RW model did not achieve adequate forecasting models for the share prices of the banking sectors hence giving evidence to suggest that the share prices of the case studies do not follow random movements. In the instance of the GARCH model, it was possible to model the HSBC share prices only as it seems to present a linear seasonal component. This model presents, in some places, a horizontal delay in the forecast values and was generally not an adequate forecasting model.

The overall results provided evidence that the BPNN models were generally superior, in modelling and forecasting the share prices from the banking sector, to the models obtained using other forecasting approaches in terms of all the accuracy measures employed in this research.

Generally, employing the proposed forecasting algorithm to model and forecast the share prices from the banking sector helped obtain an improved forecasting model and, thereafter, produce accurate forecast results. This improvement was due to **1)** the feed-back and feed-forward mechanism and **2)** the two novel stages (the Prior Information and the Reduction to Parsimonious Form), which helped the modelling process of the time datasets to be easier in building an improved model.

In addition, adding the novel technical indicators Type of Turning Points of the time series (*TTPs*) and the daily Ordinal Market Sentiments (*OMSs*) as inputs when building the forecasting models for the share prices greatly improved the forecasts in terms of all the accuracy measures employed in this research. This is because the *TTPs* helps identify the turning points of the share prices movements and the *OMSs* helps identify the directional intensity in the share prices behaviour.

Furthermore, setting the TTP_t and the OMS_t values of the last day of the used data using the market knowledge further improved the forecast accuracy of the share prices from the banking sector. In the absence of market knowledge to set the TTP_t

and the OMS_t values, i.e. when there is no market information available, the TTP_t was set in such a way that the trinomial distribution was used with parameters based on the observed percentage of each type of turning points, while, for the OMS_t, the value of *0* was used. However, the TTP_t and the OMS_t in this case did not provide the real market knowledge and, hence, this produces unreliable forecasts in terms of the direction of the shares.

With the development of the correctly identified turning points accuracy measure which was used to further evaluate the performance of the forecasting models, the selection of an adequate forecasting model for the share prices was improved. This is because this accuracy measure provided an enhanced understanding of the underlying dynamics and fluctuations of the market. To be precise, it helps to identify when the direction of the shares will be changed in the future which is believed to be very important to the investors.

The entire framework was further examined in modelling and forecasting another time series which is the historic open share prices of Barclays Bank covering the period form 1st July 2002 until 12th September 2008. The results of this time series give further evidence to conclude that, in general, the framework proposed in this research (the forecasting algorithm, the two technical indicators, the market information as input and the accuracy measure) would improve modelling and forecasting the share prices, even when exceptional market conditions are present.

The overall results provide evidence of the superiority of the forecasting models achieved in this research, compared to the financial forecasting model published in the finance literature. These superior models were obtained using the following as inputs:

1. The historic share prices on the day, y_t, one day before, y_{t-1}, two days before, y_{t-2}, three days before, y_{t-3}.
2. Pre-processed data include the first-order linearly differences of the time series, denoted by ∇y_t, and the moving average for one week (5MA), two weeks (10MA), one month (20MA) and two months (40MA).

3. Technical indicators comprise the two novel technical indicator variables, represent the market knowledge, which are the Type of Turning Points (*TTPs*) and the Ordinal Market Sentiments (*OMSs*).

Hence, this is evidence to suggest that the inputs above are suitable for modelling and forecasting any financial time series and would provide a good starting point for future applications.

7.2 Future Work

A number of the limitations of this research can be recommended for future investigations. These limitations suggest a number of research directions that can be followed for further improvement of modelling and forecasting of share prices time series specifically and financial time series in general.

Therefore, plans for future work can address some of these limitations and extend the work further as follows:

- The proposed accuracy measures (the correctly identified turning points and the direction of the shares) were successfully used to evaluate the performance of the forecasting models and improved the selection of an adequate forecasting model.

  Therefore, constructing a forecasting software that builds BPNN models based on the above accuracy measures as the model evaluation criteria should be considered in the future to further improve the selection of an adequate forecasting model.

- The daily Ordinal Market Sentiments (*OMSs*) technical indicator variable, which was developed in this research to be used as input in building the forecasting models, was significant in building the forecasting models of the share prices. However, this input requires a daily expert opinion input to produce a one step-ahead share price forecast. This expert opinion requires high cost and effectiveness on a daily basis.

Therefore, improving a calculation of the lower frequencies of the *OMSs* (weekly, bi-weekly and monthly) could be considered to provide comparable forecast accuracy measures with these obtained using the daily *OMSs*. This is despite the fact that the lower frequencies provide acceptable accuracy measures compared to the accuracy measures of the established benchmark model. Hence, these inputs were considered as usable inputs in this research for modelling and forecasting the share prices from the banking sector.

- The proposed algorithm was developed specifically to model and forecast financial time series using neural networks. Therefore, an improvement for this algorithm could be made, to generalise it, to be suitable for other forecasting approaches.

- For further evaluation of the financial models, a financial measure should be investigated in the future in addition to the mathematical accuracy measure developed in this research.

- Given the success of the forecasting models which deal with the market under normal conditions in this research, the forecasting models which take into consideration the market when under abnormal conditions should be investigated in the future.

  This could be carried out, as an initial idea, by developing an input that takes into account the abnormal movement in the time series, i.e., for example, giving an extreme value for the abnormal movements (+3 for the positive movements and -3 for the negative movements), while other movements take the values between -1 to +1.

- Despite the success of the two proposed technical indicators (*TTPs* and *OMSs*) as inputs in modelling and forecasting the share prices, further improvements of the input data can still be investigated to achieve better share price forecasts in the future, such as:

  - Measuring the *TTPs* using different time windows such as weekly (n=5) or bi-weekly (n=10).

- Measuring the values of the *OMSs* that do not take into account the value 0 when there is a small change as there is no stable movement in the financial data.

- The proposed framework was examined successfully in modelling and forecasting the share prices of the banking sector. Therefore, in order to generalise the finding of this research, different areas of the financial application such as the share prices of the companies from the industrial sector and the exchange rate of the currencies can be investigated for further evaluation of the proposed framework.

- Since the statistical approach, in particular GARCH Model, failed to model the share price time series used in this research, other non-linear statistical approaches could be considered in the future to model and forecast the share prices. These non-linear statistical approaches may include, for example, other models from the GARCH family and State Space Models since they were previously employed in modelling and forecasting the financial time series (see, for example, Timmer and Weigend, 1997; Wei, 2002).

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Appendix A: Published Papers

Appendix A.1

Rahou, Amar, *et al. Modelling and forecasting steps of financial market volatility.* Fifth Annual Doctoral Seminar, 5th May 2006. University of Glamorgan, Wales, UK, p. 15.

Appendix A.2

Rahou, Amar, *et al. Forecasting stock price volatility: Identifying a generic set of inputs to improve share prices forecasts in the banking sector.* 14th Forecasting Financial Markets Conference: Advances for Exchange Rates, Interest Rates and Asset Management, 30th May-1st June 2007. Aix-en-Provence, France. (Electronic Copy)

Appendix A.3

Rahou, Amar, *et al. A generalized algorithm for modelling & forecasting the share prices of the banking sector.* The World Congress on Engineering 2007: The 2007 International Conference of Computational Statistics and Data Engineering, 2nd-4th July 2007. London, UK. Vol. II, p. 948-955.

Appendix A.4

Rahou, Amar, *et al. Inputs to improve the share price forecasts of the banking sector.* The 18th Annual International Symposium of Forecasting. 22nd-25th June 2008. Nice, France, p. 20.

Modelling and Forecasting Steps of Financial Market Volatility

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Abstract
The financial market usually suffers high volatilities in its prices. This is because the prices in the market are affected by many factors such as economic, political, investors' behaviour and company's performance factors in general. Financial market volatility represents a major part of the systematic risk faced by investors who hold a market portfolio. Many investors (people or companies) observe the market closely when they buy or sell shares because of the future uncertainty in the prices of the shares. Hence, reliably forecasting the future values of shares is essential to minimize the risk for the investors. While some approaches have been successful in modelling certain datasets, the success of a forecasting model of financial time series does not guarantee its success with another financial time series. Hence, there is no standard forecasting procedure or technique that can be used in modelling and forecasting share prices. This research is concerned with the development of a forecasting algorithm that can be applied in modelling and forecasting financial time series. While it does not identify a superior modelling approach, it presents five steps that can be used to obtain an adequate model. These steps are data selection, data preparation, training model, testing model, and forecast production. These building steps were used to build a suitable financial forecasting model for HSBC Bank Plc. from 1st July 2000 until 30th June 2005. The model obtained yielded a one step ahead MAPE of 0.8179 and turning point prediction sensitivity of 55% and specificity of 65%.

Inputs to Improve the Forecast Accuracy of Share Prices in the Banking Sector

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Abstract

The reliable modelling and forecasting of the stock market remains a challenge because of the high volatility in individual stock prices and the market itself. This subject has received much attention in the finance literature since forecast errors represent the systematic risk faced by investors who hold a market portfolio. Hence, the ability to reliably forecast the future values of shares would provide essential help in reducing the risk to those investors who use information about the expected future direction of share movement as well as the share prices themselves in their investment decisions. This research is concerned with obtaining a set of inputs that are salient to financial data and hence can inform and improve the forecast-ability of financial forecasting models for the banking sector. In addition, a context-aware forecast evaluation approach has been developed to evaluate the performance of the forecasting models in this research. The share prices of HSBC, Lloyds TSB and the Royal Bank of Scotland were chosen in this research as case studies and ANN was chosen to forecast the future share prices for these banks for one day-ahead. Empirical results give sufficient evidence to conclude that using the variables indicating turning points in share prices as inputs generally yield superior forecasting models for datasets from the banking sector, and outstanding forecasts were achieved by using the market knowledge as an input.

1. Introduction

Financial markets often suffer high volatility in their share prices. This is because of the relatively high number of variables that may influence prices in the market including, for example, economic factors, changing political climates, company performance, supply and demand and investors' behaviour in general (Chatfield, 1996).

The systematic risk faced by investors is often related to this volatility in the financial market. Many investors (either as individual people or companies) attempt to predict future price changes by observing the market closely because of future uncertainty in the movement of shares. Hence, the ability to reliably forecast the future values of the shares (under consideration for investment) would provide essential help in reducing the risk to the investors. Hence, any successful stock price forecasting method would be of benefit to investors as it would help them in making the right investment decisions.

Some forecasting models built using different types of inputs have been successful in forecasting individual financial market datasets (see for example, Chan *et al.*, 2000; Yao and Poh, 1995). However, their findings cannot be generalised since the success of a model in forecasting one financial time series does not guarantee its success with another.

This research is concerned with identifying a set of inputs that are salient to financial data and hence can inform and improve the forecast-ability of financial forecasting models for the banking sector. The inputs considered include binary turning points indicator variables, variables representing the type of turning points (maxima and minima) and market knowledge.

Previous studies (for example, Kamruzzaman and Sarker, 2004; Yao and Tan, 2000) argue that acceptable forecasting models can be built without using market knowledge. However, it is expected that using market knowledge as an input when building the forecasting model leads to improving the forecasts of the financial market.

In addition, a forecast evaluation approach that is more suited to financial data was developed in this research to be used in evaluating the performance of the forecasting models and to aid in the model selection process. Hence, the sensitivity and specificity of predicted turning points in the time series were developed and used in this study, alongside conventional accuracy measures, to evaluate the performance of the models.

The share prices of HSBC, Lloyds TSB and the Royal Bank of Scotland were chosen in this research as case studies. These banks are global banks and their shares are held by a large number of shareholders and regularly traded. Therefore, they are suitable as case studies in this research in that they provide a wealth of potential data to mine.

The Back-Propagation Neural Network was chosen in this research to analyse the data and forecast the future share prices of the banking sector. It is an established Neural Network forecasting method and has been shown to yield reliable forecasts in business and financial applications (Chatfield, 1996; Yao *et al.*, 2000).

The remainder of the paper is organized as follows: the next section describes the input data which were used when building the forecasting models and the proposed inputs which may possibly affect the output positively. Section three illustrates the evaluation approach which was used to evaluate the performance of the built forecasting models. Section four focuses on the stages of building the forecasting models and the results of companies from the banking sector; moreover, this section shows how the market knowledge was used as input to forecast the future values of the shares. Finally, section five provides the concluding comments.

2. Data Preparation

After collecting the data and before feeding it into the network to build the forecasting model, the data has to undergo several pre-processing operations (Gately, 1996; Pyle, 1999) in order to increase the quality of the data. The pre-processing techniques used in this research include linear differencing, normalization, and moving average.

Another set of inputs used when building the forecasting model was technical indicators. Technical indicators are usually used to depict a time series (Bodis, 2004) which has high volatilities in its movement by removing noise, outliers, and other variability. Generally, technical indicators re-assemble all the information that is derived by applying some mathematical transformations to the data. It can be useful in, for example, understanding the general movement of the time series. The technical indicators used in this research (as explored in Yao and Poh, 1995) are the relative strength index (RSI), the stochastic (%K) and the moving average of stochastic (%D). In addition, the innovative technical indicator utilised in this research is the turning points (TPs).

Turning points can be generally defined as the changing points in the direction of the time series (Farnum and Stanton, 1989; Makridakis *et al.*, 1998). Hence, a turning points variable can be an important indicator which can be used as input when building the forecasting model.

Turning points of the share prices were used as an input to forecast the future share prices of the banking sector. It is expected that using the turning points as input provides important information that the network can use in building the forecasting model.

The binary turning point technical indicator variable in period n was obtained from:

$$binary\,TP_t = \begin{cases} 1 & y_{t-n},\ldots\ldots,y_{t-1} < y_t > y_{t+1},\ldots\ldots,y_{t+n} \\ 1 & y_{t-n},\ldots\ldots,y_{t-1} > y_t < y_{t+1},\ldots\ldots,y_{t+n} \\ 0 & otherwise \end{cases} \qquad (1)$$

where n is the turning points time window.

However, there are two types of turning points, maxima and minima. The maxima turning point is generated at time t when there are lower values each side of time t while the minima turning point is generated at time t when there are higher values each side of time t.

Therefore, the type of turning point technical indicator variable in period n can be obtained from:

$$type\,of\,TP_t = \begin{cases} +1 & y_{t-n},\ldots\ldots,y_{t-1} < y_t > y_{t+1},\ldots\ldots,y_{t+n} \\ -1 & y_{t-n},\ldots\ldots,y_{t-1} > y_t < y_{t+1},\ldots\ldots,y_{t+n} \\ 0 & otherwise \end{cases} \qquad (2)$$

3. Forecast Evaluation

Due to the nature of the application, the established Root Mean Square Error (RMSE) is not on its own sufficient to evaluate the performance of the forecasting model. Therefore, the sensitivity and the specificity of predicted turning points were developed in this research to be an aid in the model selection process.

Sensitivity refers to the percentage of correctly identified turning points to the total number of turning points of each type (maxima +1, minima -1, and no turning points 0), while the specificity refers to the percentage of non-correctly identified turning points to the total number of non-correctly turning points of each type, as shown in Table 1 below.

		Actual Turning Points		
		+1	**-1**	**0**
Forecasted Turning Points	**+1**	*A*	*B*	*C*
	-1	*D*	***E***	*F*
	0	*G*	*H*	***I***

Table 1: Sensitivity and Specificity of Correctly Identified Turning Points

These are obtained from:

The sensitivity and specificity of predicted maxima turning points are obtained:

$$\textit{Sensitivity of Predicted Maxima Turning Points} = \frac{A}{A+D+G} \quad (3)$$

$$\textit{Specificity of Predicted Maxima Turning Points} = \frac{E+I}{B+C+E+F+H+I} \quad (4)$$

The sensitivity and specificity of predicted minima turning points are obtained:

$$\textit{Sensitivity of Predicted Minima Turning Points} = \frac{E}{B+E+H} \quad (5)$$

$$\textit{Specificity of Predicted Minima Turning Points} = \frac{A+I}{A+C+D+F+G+I} \quad (6)$$

The sensitivity and specificity of predicted no turning points are obtained:

$$\textit{Sensitivity of Predicted no Turning Points} = \frac{I}{C+F+I} \quad (7)$$

$$\textit{Specificity of Predicted no Turning Points} = \frac{A+E}{A+B+D+E+G+H} \quad (8)$$

In general, obtaining high percentages of the sensitivity and specificity of predicted turning points implies that an adequate forecasting model has been built.

4. Application

4.1 Building the forecasting models

The historic daily open share prices of HSBC, Lloyds TSB, and the Royal Bank of Scotland covering the period 3rd of July 2000 until 24th of June 2005 were used as case studies in this research. The data was obtained from Yahoo Finance (Yahoo Finance Website).

The main aim of this research was to evaluate the adequacy of the one step-ahead models built using the proposed inputs. Back-Propagation Neural Network was used to model the datasets.

A number of missing observations were identified in the data. These missing data were estimated by taking the average of the two nearest neighbours. This is so that the missing value is estimated from data generated under market conditions that are likely to be similar to the market conditions underlying the missing observations.

Share prices in public holidays[(1)] were treated as missing values and replaced by the close share prices of the previous trading day, so that:

$$\hat{Y}_{t,holiday} = y_{t-1,previous\,close\,price} \tag{9}$$

The historic daily share prices of the case studies were normalized and pre-processed prior to including them as inputs to the forecasting models. The input data considered were the share prices on the day (y_t), share prices for one day before (y_{t-1}), share prices for two days before (y_{t-2}), share prices for three days before (y_{t-3}), share prices for four days before (y_{t-4}), first order and second order linearly differenced data, and a number of moving average series obtained using different time windows.

The data used for training in this application covers the period between 3rd of July 2000 until 31st of Dec. 2004.

A number of forecasting models were built to forecast the future share prices for the chosen banks. The selection criterion of an initial forecasting model for each bank was minimizing the RMSE. The results from the initial models selected are shown in Table 2.

For HSBC Bank Plc., the selected model was built by using 11 inputs (y_{t-4}, y_{t-3}, y_{t-2}, y_{t-1}, y_t, 5MA[(2)], 10MA, 20MA, 40MA, first-order linearly differencing, and RSI) and 9 neurons in one hidden layer. For Lloyds TSB Bank, the selected model was built by using 10 inputs (y_{t-4}, y_{t-3}, y_{t-2}, y_{t-1}, y_t, 5MA, 10MA, 20MA, 40MA, and first-order linearly differencing) and 10 neurons in one hidden layer. For Royal Bank of Scotland, the selected model was built by using 14 inputs (y_{t-4}, y_{t-3}, y_{t-2}, y_{t-}

(1) Public holidays include Christmas day, Easter day and bank holidays.

(2) The notation is that the window size of the moving average indicates the period of which the moving average is a summary of. For example, the moving average for one working week is denoted by ($5MA_t$), while the moving average for two working weeks is denoted by ($10MA_t$), and so on.

$_1$, y_t, 5MA, 10MA, 20MA, 40MA, first-order linearly differencing, second-order linearly differencing, RSI, %K, and %D) and 15 neurons in one hidden layer.

In terms of the RMSE, these models, as can be seen in Table 2, might be considered acceptable compared to the models published in the literature (for example, Anastasakis and Mort, 2004; Yu, 2002). However, these models are weak in terms of the sensitivity and specificity of predicted turning points. In short, these models fail to capture the turning points in the data.

The binary turning points variable obtained from Equation 1 using 'n=1' was added to the three models as input. This input yielded reductions in the one step-ahead forecast RMSE of 5%, 4%, and 5% for HSBC, Lloyds TSB, and Royal Bank of Scotland respectively. Moreover, a significant increase in the sensitivity and specificity of predicted maxima, minima, and no turning points were obtained from the models built after including a new input, as shown in Table 3.

Following the encouraging results above and to further improve the forecasts, the more informative type of turning points variable obtained from Equation 2 with 'n=1' was used instead of the binary turning points variable. The models built showed no strong change in terms of the RMSE and specificity of predicted turning points compared to the previous models, but the sensitivity of predicted maxima turning point increased by 53%, 55%, and 34%; sensitivity of predicted minima turning point increased by 18%, 9%, and 13% for HSBC, Lloyds TSB, and Royal Bank of Scotland respectively. However, using the type of turning points variable as input led to a slight decrease in the sensitivity of predicted no turning points compared with the models built by using the binary turning points variable.

In general, the latest models were superior compared to the models built without using the turning points as input, as shown in Table 4.

It can be seen from the graph, an example of which is shown in Figure 1, that the data are generally well-fitted by the model. Moreover, there are simple lags in certain places between the actual values and the forecast values.

The historic daily open share prices of the case study datasets covering the period 3rd of January 2005 to 24th of June 2005 were used for testing the trained models. The testing step, shown in Table 5, gave superior results in terms of RMSE and sensitivity and specificity of the predicted turning points compared to the training stage.

4.2 Forecasting Results

After obtaining acceptable forecasting models at the training and testing stages, these models were used to produce the forecasts of the daily open share prices for one day-ahead. A summary of these results is introduced below.

To test the models, the forecasted share prices of 27th June until 1st July 2005 were produced using the historic data from 3rd July 2000 until 24th June 2005. To this end, a rolling forecast was produced, so that the actual share price of 27th June 2005 was added to the input data to forecast the share prices of 28th June 2005, and so on until the forecasted share prices of 1st July 2005 was obtained.

It can be seen from Figures 2, 3 & 4 that the forecasts produced in the same direction of the actual prices in the majority of cases with the exception of 29th June 05 in HSBC, 1st July 05 in Lloyds TSB, and 29th June 2005 and 30th June 2005 in Royal Bank of Scotland. Therefore, the models succeeded in forecasting the future share prices of the companies in the banking sector.

The proposed forecasting process requires generating the turning point of the last day of the used historic data instead of the market knowledge when no information is available from the market. This is because the turning point of the last day of the used input data is unknown. In this application, this was done by simulating the experts' opinions to use it as input when forecasting the future share prices. Hence, simulated turning points generated using the binomial and trinomial distributions with parameters based on the observed percentages of the turning points were used. Then these generated turning points, which resemble the last day of the used input data, were added to the available data to forecast the next day's share price.

4.3 Using the Market Knowledge

Ideally, the models need to employ market knowledge as an input to predict whether there will be a turning point or not in the last day of input data. Below are some examples illustrating how such market knowledge may be used.

HSBC Bank Plc. agreed in the first week of February 2005 to sell its building in Singapore to Capita Commercial Trust (CCT) and subsequently leased it for a period of seven years (HSBC Bank Website). This agreement positively affected the share price. Forecasting the share price for the next trading day, 7th February 2005, required the type of turning point to be specified in the previous trading day, 4th February 2005. The share price on 4th February was going up and it was expected that the share price on 7th February would continue to go up. Therefore, there was no turning point for the last day of used data and the value of (0) was used.

The result, by using the process above, shows that the forecasted share price of 7th February 2005 has gone up on the previous trading day, as shown in Table 6.

Lloyds TSB Bank announced on 3rd March 2005 that its profits had dropped by 20% compared with profits in the previous financial year, but this drop was less than expected (BBC News Website). Therefore, the share price in this case was likely to go up. The share price on 3rd March was coming down and it was expected that the share price on 4th March would go up. Therefore, the type of turning point used for the last day of used data is the minima turning point (-1) indicating a change in the direction of the shares.

The result, shown in Table 7, shows that the forecasted share price of 4th March 2005 has gone up compared to the value in the previous trading day.

Another typical example of the use of market knowledge in setting the turning points of the input is when the Royal Bank of Scotland announced on 21st April 2005 a director change as new experience was brought in (Interactive Investor Website). The share price on 20th April 2005 was going up and it was expected that the share price on 21st April was likely to come down. Therefore, the type of turning point used for the last day of used data is the maxima turning point (+1) indicating a change in the direction of the shares.

The result, shown in Table 8, shows that the forecasted share price of 21st April 2005 has come down, i.e. in the same direction of the actual share prices.

These results that were obtained using a sample of market knowledge show that the models produced share prices in the same direction of the actual share prices. This indicates that the models have some potential.

It is worth noting that in general, the forecasting process of the open share prices for one day-ahead has to be done early enough to buy or sell before the market closes as otherwise any price movements will already have taken place when the market opens the next day.

5. Conclusions

The overall results provide evidence that superior forecasting models to forecast the future share prices of the banking sector for one day-ahead were obtained using y_{t-4}, y_{t-3}, y_{t-2}, y_{t-1}, y_t, 5MA, 10MA, 20MA, 40MA, and first-order linearly differenced data.

Using the type of turning points variable as an input did improve the forecasting models of the share prices in the banking sector.

In addition, using market knowledge to determine the type of turning points in the last day of the used data further improves the forecasts of the share prices in the banking sector.

The context-awareness of using the sensitivity and specificity of predicted maxima, minima, and no turning points, in addition to the RMSE, is beneficial to the selection of the forecasting model for the share prices of the banking sector. This selection was improved as it did not incorporate the generalized accuracy measure which can be misleading.

Banks	RMSE	Sensitivity of predicted maxima turning points	Sensitivity of predicted minima turning points	Sensitivity of predicted no turning points	Specificity of predicted maxima turning points	Specificity of predicted minima turning points	Specificity of predicted no turning points
HSBC	0.0413 (12.6905)	3%	3%	44%	32%	32%	3%
Lloyds TSB	0.0533 (17.2190)	0%	0%	51%	34%	34%	0%
Royal BK Scotland	0.0611 (33.3803)	1%	1%	51%	34%	34%	1%

Table 2: Results of the concluding trained models for the chosen banks

This table shows that acceptable forecasting models were obtained in terms of RMSE, but they were considered unacceptable in terms of the sensitivity and specificity of predicted turning points. Therefore, theses models fail to capture the turning points in the data. The normalized RMSE are listed and the actual RMSE are listed in brackets.

Banks	RMSE	Sensitivity of predicted maxima turning points	Sensitivity of predicted minima turning points	Sensitivity of predicted no turning points	Specificity of predicted maxima turning points	Specificity of predicted minima turning points	Specificity of predicted no turning points
HSBC	0.0334 (10.2695)	36%	45%	54%	52%	49%	39%
Lloyds TSB	0.0392 (12.6668)	40%	56%	52%	56%	50%	43%
Royal BK Scotland	0.0491 (26.8017)	44%	48%	55%	53%	51%	46%

Table 3: Results of the concluding models for the chosen banks after adding the binary turning points variable as input

This table shows that acceptable models were obtained in terms of the sensitivity and specificity of predicted maxima, minima, and no turning points after adding the binary turning points as input. This input yielded reductions in the RMSE and a significant increase in the sensitivity and specificity of predicted maxima, minima, and no turning points.

Banks	RMSE	Sensitivity of predicted maxima turning points	Sensitivity of predicted minima turning points	Sensitivity of predicted no turning points	Specificity of predicted maxima turning points	Specificity of predicted minima turning points	Specificity of predicted no turning points
HSBC	0.0338 (10.3818)	55%	53%	49%	54%	54%	46%
Lloyds TSB	0.0365 (11.7984)	62%	61%	43%	54%	54%	48%
Royal BK Scotland	0.0503 (27.4733)	59%	54%	47%	53%	54%	48%

Table 4: Results of the concluding models for the chosen banks using the type of turning points variable as input

This table shows that superior models were obtained in terms of the sensitivity and specificity of predicted maxima, minima, and no turning points after using the type of turning points as input instead of the binary turning points.

Banks	RMSE	Sensitivity of predicted maxima turning points	Sensitivity of predicted minima turning points	Sensitivity of predicted no turning points	Specificity of predicted maxima turning points	Specificity of predicted minima turning points	Specificity of predicted no turning points
HSBC	0.0236 (7.2663)	74%	81%	41%	62%	59%	57%
Lloyds TSB	0.0203 (6.5513)	46%	88%	31%	56%	43%	41%
Royal BK Scotland	0.0297 (16.2115)	64%	72%	28%	51%	44%	42%

Table 5: Results when testing the concluding models

This table shows that the concluding forecasting models gave superior results in terms of RMSE and the sensitivity and specificity of the predicted maxima, minima, and no turning points compared to the training models.

Date	Actual Share Prices	Forecasted Share Prices
4th Feb. 2005	876.00	–
7th Feb. 2005	892.00	**884.94**

Table 6: Actual and forecast daily open share price obtained for HSBC Bank Plc. in 4th March 2005 using the market knowledge

This table shows that the forecasting model produced a share price on 7th February 2005 in the same direction of the actual share price after using the market knowledge as input.

Date	Actual Share Prices	Forecasted Share Prices
3rd March 2005	488.50	–
4th March 2005	500.00	**491.63**

Table 7: Actual and forecast daily open share price obtained for Lloyds TSB Bank in 4th March 2005 using the market knowledge

This table shows that the forecasting model produced a share price on 4th March 2005 in the same direction of the actual share price after using the market knowledge as input.

Date	Actual Share Prices	Forecasted Share Prices
20th April 2005	1623.00	–
21st April 2005	1600.00	**1586.98**

Table 8: Actual and forecast daily open share price obtained for Royal Bank of Scotland in 21st April 2005 using the market knowledge

This table shows that the forecasting model produced a share price on 21st April 2005 in the same direction of the actual share price after using the market knowledge as input.

Figure 1: Actual and forecast daily open share prices for training the daily share prices of HSBC Bank Plc. This graph shows that the data are generally well-fitted by the model

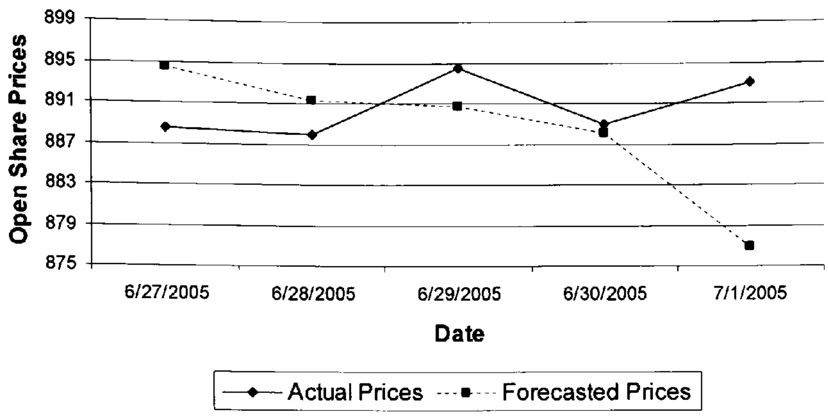

Figure 2: Actual and genuine out of sample forecast daily open share prices for HSBC Bank Plc. for the last week of June 2005

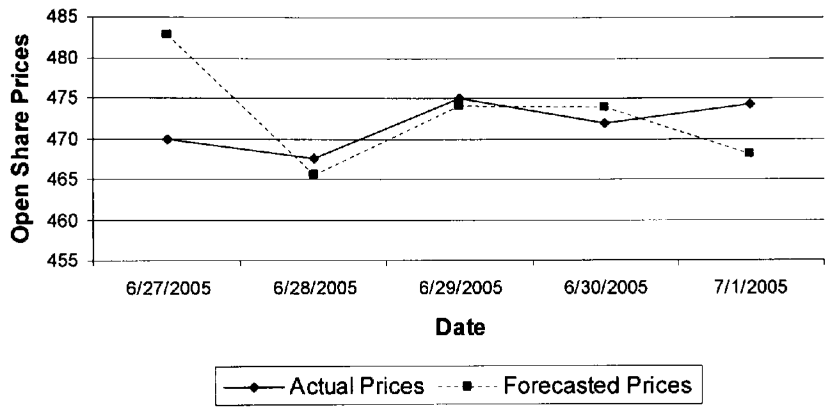

Figure 3: Actual and genuine out of sample forecast daily open share prices for Lloyds TSB Bank for the last week of June 2005

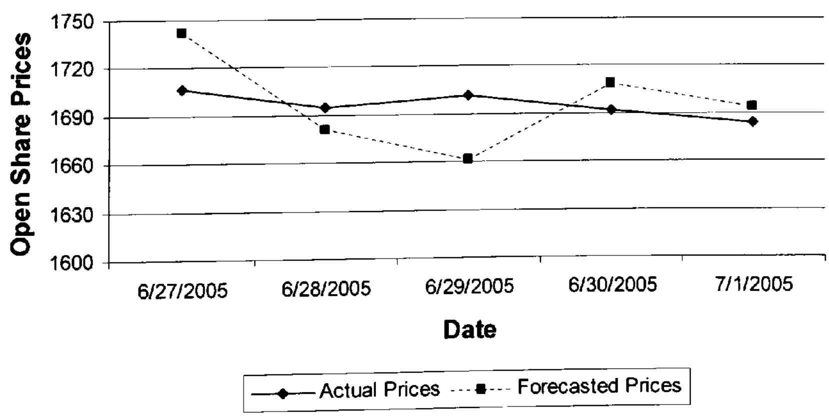

Figure 4: Actual and genuine out of sample forecast daily open share prices for Royal Bank of Scotland for the last week of June 2005

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A Generalized Algorithm for Modelling & Forecasting the Share Prices of the Banking Sector

Amar A. Majeed Rahou, Hasan Al-Madfai, Hugh Coombs, Dave Gilleland, and Andrew Ware

Abstract—**The issue of modelling and forecasting the share prices of the banking sector remains a challenge because of high volatilities in individual stock prices. Reliably forecasting the future values of shares is essential to minimize the risk for investors, but there is currently no standard forecasting procedure or technique that can be used in modelling and forecasting the share prices of the banking sector. This research is concerned with the development of a forecasting algorithm that can be applied in modelling and forecasting the share prices of the banking sector. It proposes six steps that, when followed, may lead to obtaining superior models. These steps are Data Selection, Data Preparation, Training the Model, Refining the Model, Testing the Model, and Forecast Production. These building steps were used to build a forecasting model for HSBC Bank Plc. and Lloyds TSB using the Back-propagation Neural Network. Empirical results show that superior models were obtained by applying the proposed algorithm compared to the financial forecasting models published in the literature.**

Index Terms—**forecasting algorithm, financial forecasting, banking sector, neural network.**

I. INTRODUCTION

Modelling and forecasting shares in the banking sector has received much attention in the finance literature because of the high volatilities in its prices which represents a systematic risk faced by investors who hold these shares in their market. This is because the prices in the market are affected by many factors such as the economic and political climate, company's performance, supply and demand and investors' behaviour in general. Many investors observe the market closely when they buy or sell shares because of the future uncertainty in the prices of the shares. Hence, reliably forecasting the future values of shares is essential to minimize the risk for the investors. While some approaches have been successful in modelling certain datasets, the success of a forecasting model on a time series does not guarantee its success with another. Hence, there is no standard forecasting procedure or technique that can be used in modelling and forecasting the share prices of the banking sector.

One notable work attempting to address this issue is the algorithm proposed by Yao & Tan [10]. However, applying their proposed algorithm was not always enough to arrive at an adequate forecasting model. This may be because the proposed steps do not include feed-back and feed-forward mechanisms to update the input data or the forecasting approach used to build the forecasting model when an insufficiently accurate model is obtained.

This research is concerned with the development of a generalized forecasting algorithm that can be applied in modelling and forecasting the share prices of the banking sector.

II. PROPOSED ALGORITHM

The flowchart of the proposed algorithm is given in Fig. 1. It can be seen from Fig. 1 that the algorithm consists of six steps, with feed-back and feed-forward loops. The following sections introduce the modelling and forecasting steps proposed by the algorithm.

A. Data Selection

The first step of the modelling and forecasting process is selecting, from the available data, the inputs to be used in building the forecasting model. All the relevant or possibly relevant data to the target should be investigated for possible inclusion. The most common data which is pertinent to the banking sector are the historic share prices, the factors that affect share prices, and the historic financial statements of the companies.

It is proposed that this step consists of three main stages, as follows:

1. Prior Information

Prior information refers to all the relevant information available at the beginning of the forecasting model building process. In addition to the related data which is mentioned above, prior information may include:

- Available forecasting approaches that can be used to forecast the share prices,
- Available experience and knowledge, and
- Available tools such as software and facilities.

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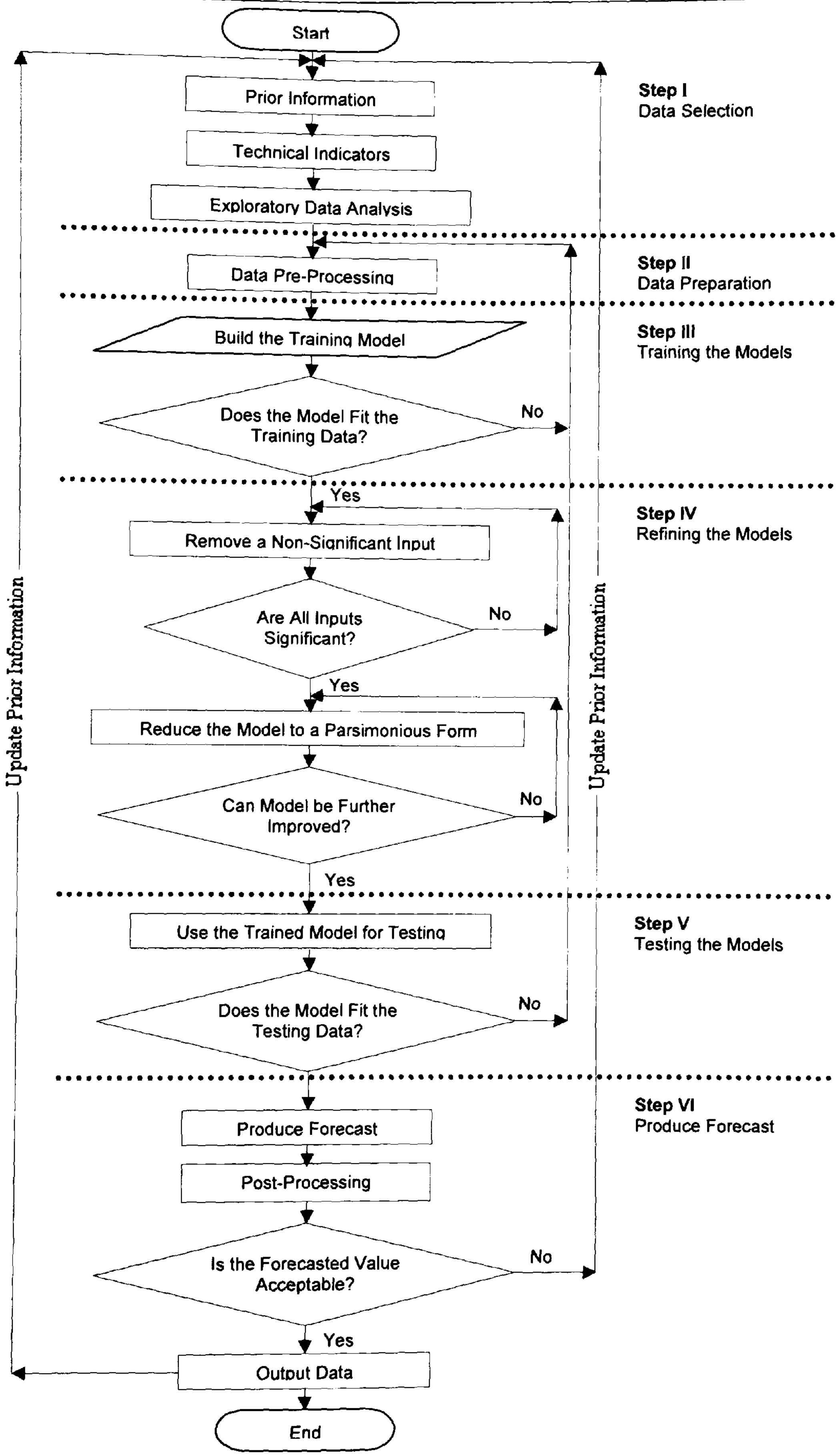

Figure 1: Forecasting Model Building Algorithm

Which of these to be used in modelling can be determined by using evidence from the literature and the analysts' own experience.

2. Technical Indicators

Usually technical indicators are used to depict a time series, those with high volatility in their movements, by removing noise, outliers, and other sources of variation. In general, technical indicators re-assemble all the information that is derived by applying some mathematical transformations to the data in a time series. They can be useful in understanding the general movement of the time series.

For example, one important technical indicator in financial time series is turning points, generally defined as the changing points in the direction of the time series [2], [7] can be used as an input when building the forecasting model to help build improved forecasting models.

The binary turning point in period n variable can be obtained from:

$$TP_t = \begin{cases} 1 & y_{t-n},\ldots\ldots,y_{t-1} < y_t > y_{t+1},\ldots\ldots,y_{t+n} \\ 1 & y_{t-n},\ldots\ldots,y_{t-1} > y_t < y_{t+1},\ldots\ldots,y_{t+n} \\ 0 & otherwise \end{cases}$$

where n is the turning points time window.

As there are two types of turning points, maxima and minima, where the maxima turning point is generated at time t when there are lower values in each side of time t while the minima turning point is generated at time t when there are higher values in each side of time t.

Therefore, the type of turning point technical indicator variable in period n can be obtained from:

$$TP_t = \begin{cases} +1 & y_{t-n},\ldots\ldots,y_{t-1} < y_t > y_{t+1},\ldots\ldots,y_{t+n} \\ -1 & y_{t-n},\ldots\ldots,y_{t-1} > y_t < y_{t+1},\ldots\ldots,y_{t+n} \\ 0 & otherwise \end{cases}$$

3. Exploratory Data Analysis

Exploratory data analysis (EDA) is an important step in time series analysis. It provides an exploration of the data before starting with the forecasting process. The first step of EDA is usually plotting the time series against time to obtain an overview of the dataset. This step is useful to identify anomalies such as missing data and outliers.

Other EDA techniques involve plotting the autocorrelation function (ACF) and partial autocorrelation function (PACF) to identify if the time series was seasonal and the periodicity of that seasonality.

B. Data Preparation

After collecting the data and prior to building the forecasting model, the data is usually subjected to several pre-processing operations. This is normally carried out to increase the quality of the data since the success of any forecasting model depends on the quality of the input data.

Common data preparation and pre-processing techniques include:

1. Linear Differencing

Linear differencing is a pre-processing technique which is used to measure the difference between the values in a time series separated by a specific time period. It is often used to remove the trend and seasonality in time series data [1].

First-order linear differencing is obtained by subtracting the value at time t and the immediately preceding value at time t-1 [7]. Analytically it is obtained from:

$$\nabla y_t = y_t - y_{t-1} \qquad (1)$$

Seasonal differencing is calculated by subtracting the value at time t and the corresponding preceding value at time t-s, according to the seasonal period [7], where s is the periodicity of the seasonal component of the data. Analytically it is obtained from:

$$\nabla_s y_t = y_t - y_{t-n} \qquad (2)$$

Some studies refer to the differenced dataset as the "momentum" of the shares; see for example [11].

2. Normalization

Normalization is a pre-processing technique obtained using the standard deviation and the average of the dataset. It is useful to decrease the absolute range of the values of a time series.

For a given value y_t, its normalized value can be obtained from:

$$z_t = \frac{y_t - \bar{y}}{SD} \qquad (3)$$

where,

$\bar{y}$ the mean value of the dataset

SD the standard deviation

Normalization often fails when the mean is unrepresentative of the data, such as when there is a linear trend in the time series.

3. Data Smoothing

Smoothing the data may be useful in understanding the fundamental trend of the data i.e. to reduce the noise and random components of the data.

Many methods can be used to smooth the data including the Crude Moving Average. This is an established and widely-used technique to smooth data [3], [4], [8].

In time series analysis there are two types of moving average; these are the centred moving average (CMA) and the prior moving average (PMA) [5], [7].

The calculation used in the CMA is dependent on the numbers of values in the time window that is selected to calculate the moving average. This calculation is subject to whether the number of observations is odd or even (see [7] for details).

The main difference is that CMA is centred in the middle of the selected data, whilst the PMA is positioned next to the last number.

CMA for an odd number of observations is obtained from:

$$CMA_t = \frac{1}{n} \sum_{j=-((n-1)/2)}^{((n-1)/2)} y_{t+j} \qquad (4)$$

where n is the moving average time window.

While the CMA for an even number of observations is obtained from:

$$CMA_t = \frac{1}{2(n-1)} \left(\sum_{j=-(n/2)}^{(n/2)-1} y_{t+j} + \sum_{j=-(n/2)+1}^{(n/2)} y_{t+j} \right) \qquad (5)$$

The PMA is obtained from:

$$PMA_t = \frac{1}{n} \sum_{t=1}^{n} y_t \qquad (6)$$

PMA is generally used to smooth time series data. This is because it depends only on the past observations while, by contrast, calculating the centred moving average depends on the past and future observations.

C. Training the Models

The initial stage of this process is to choose the size of the dataset required to train the model. It is generally, the case that a large proportion of the available data is used for training and the remaining smaller proportion is used for testing.

Model training is generally performed in two steps: the first step fits the model using the given inputs, and the second step verifies the validity of the model by comparing within sample forecasts to the observed values.

Training the model, in the case of using neural network for example, can be done using different types of input data employing different model architectures [6], [9]. Model architecture refers to the number of input layers, hidden layers and output layers which are used to build the forecasting model. While training the model using GARCH involves finding appropriate initial estimates of the parameters and then successively refines them until the optimum values of the parameters are obtained.

In general, when the forecasting model, which is obtained, gives unacceptable results, this leads to a revisiting of the data preparation step in order to choose a different set of inputs and possibly different model. This is usually iterated until improved results are obtained.

The most significant problem to avoid in this step is over-training and over-parameterization [7], [9]. To solve this problem, a decision has to be made as when the training should stop. The point at which training stops usually depends on the forecasting accuracy measures used. For example, novel accuracy measures such as sensitivity and specificity of predicted turning points may be used, in addition to the conventional least squares error, to evaluate the performance of the forecasting models and hence avoid this problem. In this instance, sensitivity refers to the percentage of correctly identified positive values to the total number of positive values, i.e. true positive, while the specificity refers to the percentage of correctly identified negative values to the total number of negative values, i.e. true negative, as shown in Table 1 below.

Table 1: Sensitivity and Specificity of Correctly Identified Turning Points

		Actual Turning Points	
		1	0
Forecasted Turning Points	1	True Positive	False Positive
	0	False Negative	True Negative

These are obtained from:

$$Sensitivity = \frac{\sum_{t=1}^{n} TruePositive}{\sum_{t=1}^{n} (TruePositive + FalseNegative)} \qquad (7)$$

$$Specificity = \frac{\sum_{t=1}^{n} TrueNegative}{\sum_{t=1}^{n} (TrueNegative + FalsePositive)} \qquad (8)$$

D. Refining the Model

1. Remove a Non-Significant Input

This step involves removing non-significant inputs, i.e. keeping the inputs that significantly affect the output and discarding the inputs that have smaller or no affect on the output. This can be done by removing inputs one at time and evaluating the performance of the model at each step.

2. Reduce the Model to a Parsimonious Form

This is an optimization of the number of parameters and accuracy measures, so that the model would have an optimum accuracy measure with as few parameters as possible.

E. Testing the Model

Testing the model is an attempt to investigate the forecasting capability of the trained model by using a time window of the time series that was not used in building the model [8], [9]. It is conventional that a small proportion of the data is usually used for testing.

Hence, this step entails checking the trained model to ascertain whether it fits the testing data or not. If not, that leads back to the data preparation step to follow the steps again until an adequate testing model is obtained [8].

F. Producing Forecasts

After obtaining an adequate forecasting model, it can be used now to forecast the future values of the share prices.

In many cases, a post-processing step is applied to the forecasts in order to revert them back to the data's original scale. This is why it is essential that all pre-processing methods are reversible.

The forecasted values will be checked to ascertain whether they are acceptable in terms of the application. If not, the forecasting model building steps are started again from the beginning with updated prior information. This process is iterated until acceptable forecasts are obtained.

III. APPLICATION

The algorithm proposed in this paper was used to build a forecasting model for the share prices of two companies in the banking sector.

The historic daily open share prices of HSBC Bank Plc. and Lloyds TSB Bank which cover the period between 3rd of July 2000 until 24th of June 2005, as shown in Fig. 2 and Fig. 3 respectively, were used in this research. The aim was to forecast the future share prices for one day-ahead using a Back-Propagation Neural Network.

The models were Univariate, built using only the historic share prices without exogenous variables (1).

The type of turning point technical indicator variable for 'n=1' (introduces in section A.2) was investigated as input in this research. It was expected that using the turning points of the share prices as input helps to build improved forecasting models.

(1) Exogenous variables resemble for example, the evaluation of company's activities and the factors that affect share prices.

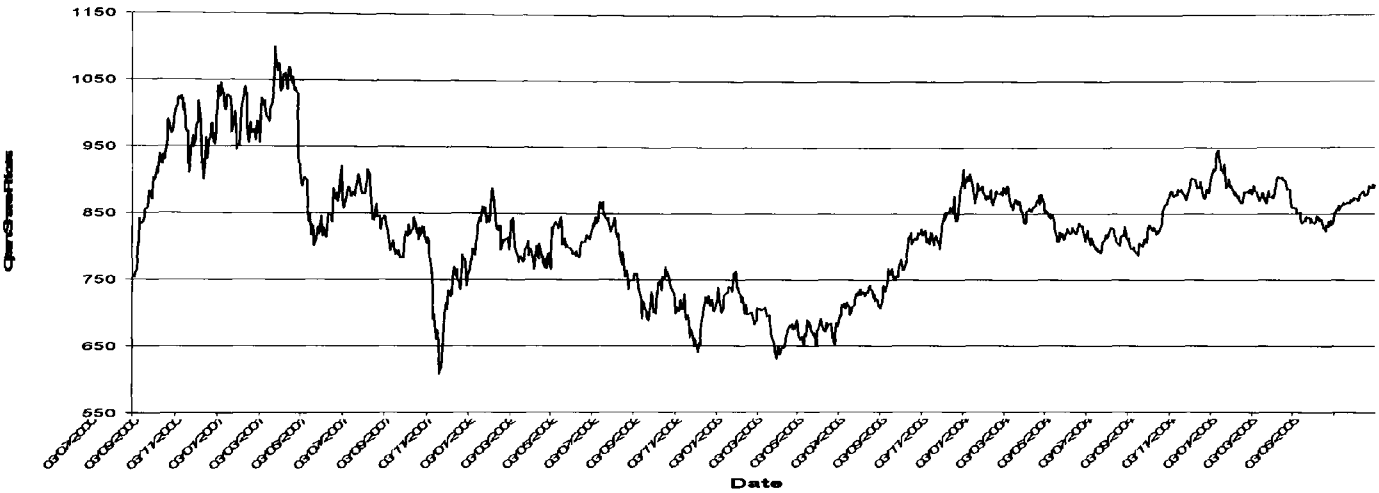

Figure 2: The historic daily share prices of HSBC Bank Plc. which cover the period between 3rd of July 2000 until 24th of June 2005

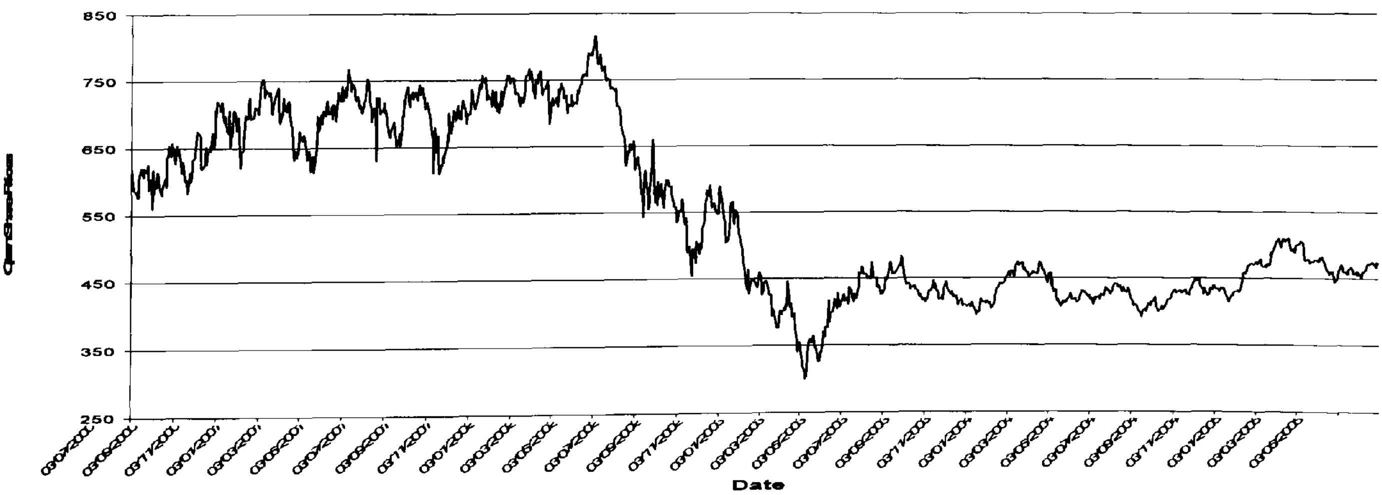

Figure 3: The historic daily share prices of Lloyds TSB Bank which cover the period between 3rd of July 2000 until 24th of June 2005

A number of missing observations were identified through EDA. The missing data were estimated by taking the average of the two nearest good neighbours, as these are likely to be similar to the market conditions underlying the missing observations.

Share values in public holidays (2) were equated to the close share prices of the previous trading day, so that

$$\hat{Y}_{t,holiday} = y_{t-1,previous\,close\,price} \quad (9)$$

The historic daily share prices of the case studies were normalized and pre-processed prior to including them as inputs to the forecasting models. The input data considered were the share prices on the day (y_t), share prices for one day before (y_{t-1}), share prices for two days before (y_{t-2}), share prices for three days before (y_{t-3}), share prices for four days before (y_{t-4}), first order and second order differenced data, and a number of moving average series obtained using different time windows.

The data used for training in this application covers the period between 3rd of July 2000 until 31st of Dec. 2004.

For HSBC Bank Plc., an initial model was selected. This model had optimum maximum percentages of the sensitivity and specificity of the predicted turning points and Root Mean Square Error (RMSE), which were 50%, 51%, and 0.0345 respectively. This model was built using 13 inputs (y_{t-4}, y_{t-3}, y_{t-2}, y_{t-1}, y_t, $5MA_t$(3), $10MA_t$, $20MA_t$, $40MA_t$, $60MA_t$, first-order differencing, Relative Strength Index (RSI) and binary turning points for 'n=1') and 14 neurons in one hidden layer.

In the refining step, the number of inputs was reduced to 12 after removing the non-significant input $60MA_t$ and reducing the number of neurons to 9 in one hidden layer. The model, after refinement, yielded sensitivity of the predicted turning points of 55%, specificity of the predicted turning points of 54% and RMSE 0.0334.

The historic daily open share prices, covering the period between 3rd of January 2005 until 24th of June 2005, were used for testing the trained model. This resulted in sensitivity of the predicted turning points of 50%, specificity of the predicted turning points of 59% and RMSE 0.0189.

The model was rebuilt using the type of turning points instead of the binary turning points as input. The forecasts obtained from this model, shown in Fig. 4, yielded a one step-ahead sensitivity of predicted point of 63% and 77% for the training and testing, specificity of predicted turning points of 49% and 41% for the training and testing, and RMSE 0.0338 and 0.0236 for training and testing respectively.

To test the models, the forecasted share prices of 27th June until 1st July 2005 were produced using the historic data from 3rd July 2000 until 24th June 2005. To this end, rolling forecast were produced, so that the actual share price of 27th June 2005 was added to the input data to forecast the share prices of 28th June 2005, and so on until the forecasted share prices of 1st July 2005 was obtained. These forecasts are shown in Table 2.

(2) Public holidays include Christmas day, Easter day and bank holidays.

(3) The notation is that the window size of the moving average indicates the period of which the moving average is a summary of. For example, the moving average for one working week is denoted by ($5MA_t$), while the moving average for two working weeks is denoted by ($10MA_t$), and so on.

Figure 4: Actual and forecast daily open share prices for training the daily share prices of HSBC Bank Plc. This graph shows that there are simple lags in certain places between the actual values and the forecast values

Table 2: Actual and forecast daily open share prices obtained for HSBC Bank Plc. in last week of June 2005

Date	Actual Share Prices	Forecasted Share Prices
27th June 2005	888.50	894.53
28th June 2005	888.00	891.26
29th June 2005	894.50	890.69
30th June 2005	889.00	888.09
1st July 2005	893.00	876.84

Fig. 5 shows that the forecasting model produced forecasts in the same direction of the actual prices.

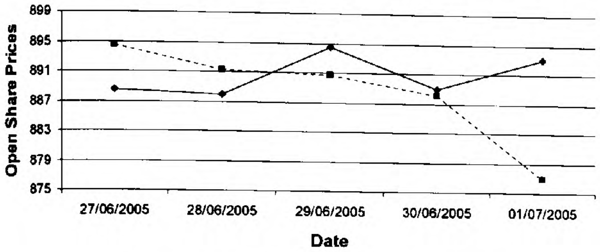

Figure 5: Actual and genuine out of sample forecast daily open share prices for HSBC Bank Plc. for the last week of June 2005.

For Lloyds TSB Bank, an initial model was selected. This model had optimum maximum percentages of the sensitivity and specificity of the predicted turning points and RMSE as 57%, 49%, and 0.0402 respectively. This model was built using 11 inputs (y_{t-4}, y_{t-3}, y_{t-2}, y_{t-1}, y_t, $5MA_t$, $10MA_t$, $20MA_t$, $40MA_t$, first-order differencing, and binary turning points for 'n=1') and 12 neurons in one hidden layer.

In the refining step, all the inputs were significant but the number of neurons in one hidden layer was reduced to 10. The model, after refinement, yielded sensitivity of the predicted turning points of 62%, specificity of the predicted turning points of 52% and RMSE 0.0392.

The historic daily open share prices, covering the period between 3rd of January 2005 until 24th of June 2005, were used for testing the trained model. This resulted in sensitivity of the predicted turning points of 60%, specificity of the predicted turning points of 41% and RMSE 0.0340.

The model was rebuilt using the type of turning points instead of the binary turning points as input. The forecasts obtained from this model, shown in Fig. 6, yielded a one step-ahead sensitivity of predicted point of 70% and 71% for the training and testing, specificity of predicted turning points of 43% and 31% for the training and testing, and RMSE 0.0365 and 0.0203 for training and testing respectively.

To test the models, the forecasted share prices of 27th June until 1st July 2005 were produced using the historic data from 3rd July 2000 until 24th June 2005. To this end, rolling forecast were produced, so that the actual share price of 27th June 2005 was added to the input data to forecast the share prices of 28th June 2005, and so on until the forecasted share prices of 1st July 2005 was obtained. These forecasts are shown in Table 3.

Table 3: Actual and forecast daily open share prices obtained for Lloyds TSB Bank in last week of June 2005

Date	Actual Share Prices	Forecasted Share Prices
27th June 2005	470.00	482.87
28th June 2005	467.50	465.54
29th June 2005	475.00	474.15
30th June 2005	472.00	473.85
1st July 2005	474.25	468.13

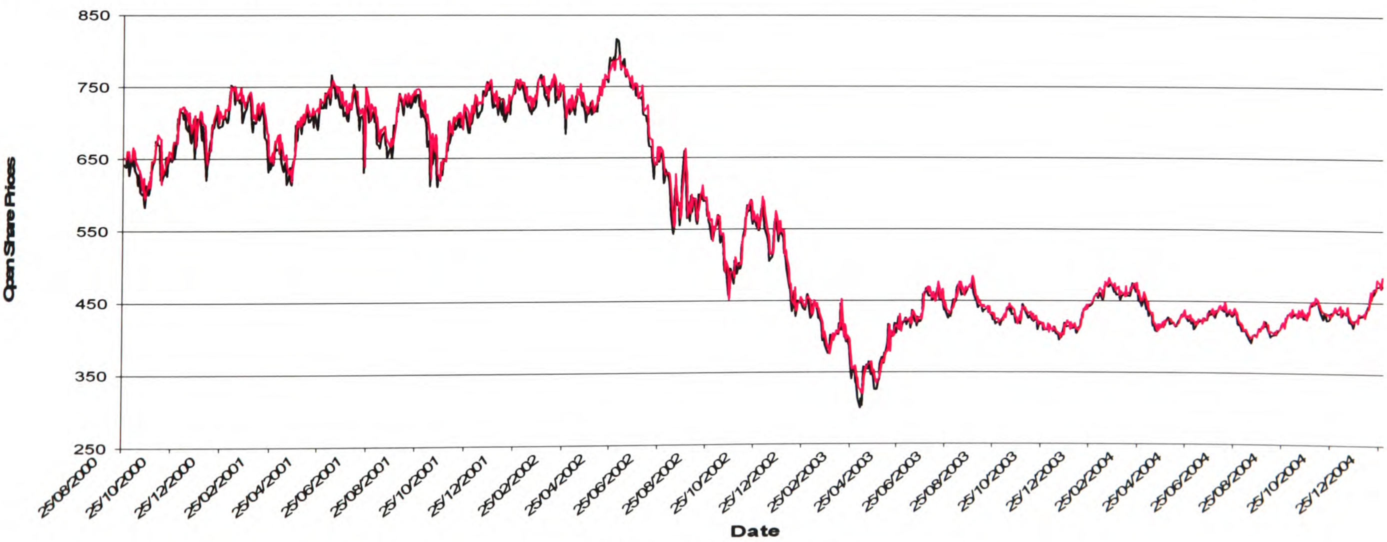

Figure 6: Actual and forecast daily open share prices for training the daily share prices of Lloyds TSB Bank. This graph shows that there are simple lags in certain places between the actual values and the forecast values

Fig. 7 shows that the forecasting model produced forecasts in the same direction of the actual prices.

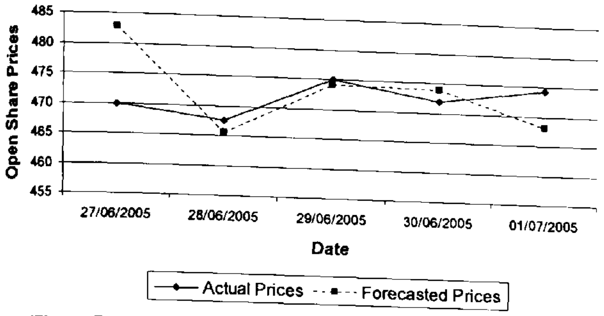

Figure7: Actual and genuine out of sample forecast daily open share prices for Lloyds TSB Bank for the last week of June 2005.

The forecasting process requires generating the turning point of the last day of the used historic data in preference to using any exogenous variables. This is because the turning point of the last day of the used input data is unknown. In this application, this was done by simulating the experts' opinion to use it as input when forecasting the future share prices. Hence, simulated turning points generated using the binomial and trinomial distributions with parameters based on the observed percentages of the turning points were used. Then these generated turning points, which resemble the last day of the used input data, were added to the available data to forecast the next day's share price.

In general, forecasting process of the open share prices for one day-ahead has to be done early enough to buy or sell before the market closes as otherwise any price movements will already have taken place when the market opens in the next day.

IV. CONCLUSIONS

The overall results provide evidence suggesting that superior models, compared to the models published in the literature, to forecast the daily open share prices of the banking sector share prices may be obtained using the proposed algorithm. The feed-back and feed-forward mechanisms proposed in the algorithm did help in building an adequate model to forecast the share prices of the banking sector. These mechanisms are used to update:

- The per-processing of the data when obtaining insufficient model from training and testing steps.
- The prior information when obtaining unacceptable forecasts.

Empirical results presented in this research give sufficient evidence to conclude that using the type of turning points variables as inputs generally yields superior forecasting models for datasets from the banking sector.

Using the accuracy measure (sensitivity and specificity of predicted turning points), in addition to the RMSE, did improve the model selection process.

This work may be further improved through using exogenous variables to determine the type of turning point for the last day of time series in stead of simulating the turning points using the binomial and trinomial distributions. It is expected that this could lead to improved forecasts in the banking sector.

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Inputs to Improve the Share Price Forecasts of the Banking Sector

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The issue of stock market modelling and forecasting remains a challenge because of the high volatilities in individual stock prices and the market itself. This topic has received much attention in the literature since forecast errors represent the systematic risk faced by investors. Hence, the ability to reliably forecast the future values of the shares would provide essential help in reducing the risk to those investors through the use of information about the direction of share price variability and historic share prices. While some forecasting models have been successful in forecasting individual financial market datasets, their findings cannot be generalised since the inputs used are often application specific, hence, the success of a model in forecasting one financial time series does not guarantee its success with another. This research is concerned with identifying a set of inputs that are salient to the banking sector and hence can inform and improve the reliability of financial forecasting for the banking sector in the UK. The ordinal market sentiment, a novel technical indicator variable is introduced in this research to be used as an input when modelling the share prices from the banking sector using an adaptive Back-propagation Neural Network, forecasting models were built to forecast the future share prices of HSBC, Lloyds TSB and the Royal Bank of Scotland. Empirical results give sufficient evidence to conclude that using the ordinal market sentiment technical indicator variable as an input generally improves the forecasting models for datasets from the banking sector in terms of the number of turning points predicted and conventional forecast accuracy measures.

Appendix B: Established Benchmark Model

This benchmark model was built by Gately (1996) using back-propagation neural network to forecast the hourly value of S&P500 index. The architecture of the network consisted of six input neurons, six neurons in one hidden layer and one output neuron. These inputs were the following:

1. New York Stock Exchange 100 index, which is the observed value of New York Stock Exchange Index.
2. S&P futures contract (SPY), is defined as an agreement of buying or selling a specific amount of stocks, currencies or any financial instruments at a particular price on a specific future date.
3. Number of NYSE advances (ADV), is defined as the number of stocks in New York Stock Exchange which are going up.
4. Number of NYSE declines (DEC), is defined as the number of stocks in New York Stock Exchange which are coming down.
5. Tick volume (TICK), is defined as a measure of market strength or weakness, it is calculated by finding the deference between the ADV and the DEC. It is given by:

$$TICK = ADV - DEC$$

6. Traders' index (TRIN), is used to detect overbought and oversold levels in the market. It is given by:

$$TRIN = \frac{\text{Advancing Issues} / \text{Declining Issues}}{\text{Advancing Volume} / \text{Declining Volume}}$$

where *Advancing Issues* is the number of stocks go up, *Declining Issues* is the number of stocks come down, *Advancing Volume* is the trading volume of stocks go up traded and *Declining Volume* is the trading volume of stocks come down.

The result, listed below, of training the back-propagation neural network forecasting model, which were published in Gately (1996, p. 23), were used to calculate the values accuracy measures employed in this research used as one of the benchmark values to evaluate the performance of the forecasting models built in this research.

	Actual Values	Forecast Values
1	448.64	449.47
2	448.23	449.78
3	448.04	450.28
4	447.94	449.82
5	448.41	449.40
6	448.66	449.76
7	449.22	449.38
8	448.38	449.01
9	447.29	448.74
10	447.57	448.38
11	447.55	448.26
12	446.92	448.75
13	446.55	448.86
14	445.75	449.20
15	446.30	447.89
16	445.31	447.08
17	445.34	447.21
18	445.18	447.22
19	445.70	446.82
20	445.85	446.51
21	446.02	445.70
22	444.22	446.58
23	445.79	446.00
24	446.75	446.21
25	447.49	446.13
26	447.08	446.39
27	447.08	446.63
28	447.31	446.76
29	446.14	445.67
30	446.48	446.85
31	446.26	447.68
32	446.46	448.27
34	446.23	447.87
35	446.39	447.98
36	447.18	447.98
37	446.44	446.43
38	447.00	446.80
39	446.76	446.77
40	446.52	447.08
41	446.20	446.86
42	444.11	446.92
43	444.51	447.52
44	446.58	446.76
45	445.79	447.43
46	445.26	446.97
47	445.27	446.89
48	446.21	446.56
49	446.83	445.07
50	447.10	445.25
51	448.75	446.61
52	448.32	445.92
53	448.42	445.57
54	448.62	445.65

Appendix C: Time Series Case Studies

Appendix C.1: *The historic open share prices of HSBC Bank covers the period from 3rd July 2000 until 30th March 2007.*

Date	Prices
03/07/2000	753.00
04/07/2000	753.50
05/07/2000	755.00
06/07/2000	753.00
07/07/2000	760.00
10/07/2000	767.00
11/07/2000	805.00
12/07/2000	805.00
13/07/2000	842.00
14/07/2000	833.00
17/07/2000	835.00
18/07/2000	835.00
19/07/2000	841.00
20/07/2000	842.00
21/07/2000	855.18
24/07/2000	856.59
25/07/2000	858.00
26/07/2000	883.00
27/07/2000	882.50
28/07/2000	882.00
31/07/2000	870.00
01/08/2000	891.00
02/08/2000	903.00
03/08/2000	899.50
04/08/2000	900.00
07/08/2000	919.00
08/08/2000	908.50
09/08/2000	923.50
10/08/2000	924.00
11/08/2000	939.00
14/08/2000	924.00
15/08/2000	924.00
16/08/2000	938.00
17/08/2000	938.00
18/08/2000	930.00
21/08/2000	951.50
22/08/2000	970.00
23/08/2000	990.00
24/08/2000	986.25
25/08/2000	980.00
28/08/2000	969.00
29/08/2000	975.00
30/08/2000	973.00
31/08/2000	984.00
01/09/2000	998.50
04/09/2000	1009.00
05/09/2000	1010.00
06/09/2000	1019.50
07/09/2000	1024.00
08/09/2000	1020.00
11/09/2000	1026.00
12/09/2000	1018.00
13/09/2000	1021.00
14/09/2000	1003.00
15/09/2000	1014.00
18/09/2000	977.00
19/09/2000	971.25
20/09/2000	973.00
21/09/2000	963.00
22/09/2000	910.00
25/09/2000	944.50
26/09/2000	950.00
27/09/2000	956.00
28/09/2000	966.00
29/09/2000	949.00
02/10/2000	962.00
03/10/2000	980.00
04/10/2000	985.00
05/10/2000	984.00
06/10/2000	1018.00
09/10/2000	988.00
10/10/2000	963.00
11/10/2000	925.00
12/10/2000	916.50
13/10/2000	900.00
16/10/2000	938.00
17/10/2000	963.00
18/10/2000	949.00
19/10/2000	931.00
20/10/2000	954.00
23/10/2000	963.00
24/10/2000	976.00
25/10/2000	985.00
26/10/2000	985.00
27/10/2000	961.00
30/10/2000	953.00
31/10/2000	974.50
01/11/2000	996.00
02/11/2000	1000.00
03/11/2000	1041.00
06/11/2000	1025.00
07/11/2000	1040.00
08/11/2000	1045.00
09/11/2000	1028.00
10/11/2000	1036.00
13/11/2000	1006.00
14/11/2000	1004.00
15/11/2000	1016.00
16/11/2000	1027.00
17/11/2000	1028.00
20/11/2000	1024.00
21/11/2000	1024.00
22/11/2000	1008.00
23/11/2000	971.00
24/11/2000	976.00
27/11/2000	994.75
28/11/2000	1002.00
29/11/2000	977.00
30/11/2000	945.00
01/12/2000	950.00
04/12/2000	950.00
05/12/2000	961.00
06/12/2000	1001.00
07/12/2000	1010.00
08/12/2000	1013.00
11/12/2000	1035.00
12/12/2000	1033.00
13/12/2000	1040.00
14/12/2000	1028.00
15/12/2000	983.00
18/12/2000	955.00
19/12/2000	972.00
20/12/2000	986.25
21/12/2000	970.39
22/12/2000	970.00
25/12/2000	975.00
26/12/2000	975.00
27/12/2000	968.00
28/12/2000	959.00
29/12/2000	988.00
01/01/2001	985.00
02/01/2001	971.00
03/01/2001	956.00
04/01/2001	998.00
05/01/2001	1023.00
08/01/2001	1011.00
09/01/2001	1019.00
10/01/2001	1010.00
11/01/2001	1004.59
12/01/2001	994.00
15/01/2001	992.25
16/01/2001	987.00
17/01/2001	994.00
18/01/2001	1010.00
19/01/2001	1010.00
22/01/2001	1023.70
23/01/2001	1043.00
24/01/2001	1071.50
25/01/2001	1100.00
26/01/2001	1082.00
29/01/2001	1064.00
30/01/2001	1071.00
31/01/2001	1075.00
01/02/2001	1059.00
02/02/2001	1033.00
05/02/2001	1040.00
06/02/2001	1059.00
07/02/2001	1058.75
08/02/2001	1058.00
09/02/2001	1060.50
12/02/2001	1035.00
13/02/2001	1052.00
14/02/2001	1069.00
15/02/2001	1069.00
16/02/2001	1062.00
19/02/2001	1045.00
20/02/2001	1055.00
21/02/2001	1047.00
22/02/2001	1034.00
23/02/2001	1038.00
26/02/2001	1030.00
27/02/2001	950.00
28/02/2001	930.50
01/03/2001	926.00
02/03/2001	911.00
05/03/2001	890.00
06/03/2001	898.00
07/03/2001	900.00
08/03/2001	904.00
09/03/2001	901.00
12/03/2001	899.00
13/03/2001	851.00
14/03/2001	843.50
15/03/2001	836.00
16/03/2001	849.00
19/03/2001	816.00
20/03/2001	832.00
21/03/2001	829.50
22/03/2001	810.00
23/03/2001	800.00
26/03/2001	813.00
27/03/2001	817.00
28/03/2001	829.00
29/03/2001	819.50
30/03/2001	818.00
02/04/2001	845.00
03/04/2001	833.00
04/04/2001	815.00
05/04/2001	816.25
06/04/2001	828.00
09/04/2001	813.00
10/04/2001	817.00
11/04/2001	839.00
12/04/2001	848.00
13/04/2001	847.00
16/04/2001	847.00
17/04/2001	839.50
18/04/2001	836.00
19/04/2001	887.00
20/04/2001	883.00
23/04/2001	869.50

24/04/2001	871.00	18/07/2001	796.00	11/10/2001	757.50	04/01/2002	838.00
25/04/2001	881.00	19/07/2001	787.50	12/10/2001	769.00	07/01/2002	843.00
26/04/2001	867.00	20/07/2001	794.00	15/10/2001	754.50	08/01/2002	824.50
27/04/2001	875.00	23/07/2001	787.00	16/10/2001	759.75	09/01/2002	816.00
30/04/2001	910.50	24/07/2001	794.00	17/10/2001	765.00	10/01/2002	800.00
01/05/2001	921.00	25/07/2001	788.00	18/10/2001	748.00	11/01/2002	796.00
02/05/2001	907.00	26/07/2001	782.04	19/10/2001	750.00	14/01/2002	787.00
03/05/2001	870.00	27/07/2001	783.00	22/10/2001	734.00	15/01/2002	776.50
04/05/2001	857.00	30/07/2001	784.78	23/10/2001	757.50	16/01/2002	784.00
07/05/2001	869.00	31/07/2001	782.00	24/10/2001	770.00	17/01/2002	783.00
08/05/2001	874.00	01/08/2001	800.00	25/10/2001	787.50	18/01/2002	786.00
09/05/2001	878.00	02/08/2001	816.00	26/10/2001	783.25	21/01/2002	777.00
10/05/2001	884.00	03/08/2001	822.00	29/10/2001	779.00	22/01/2002	777.50
11/05/2001	890.00	06/08/2001	815.00	30/10/2001	753.50	23/01/2002	783.00
14/05/2001	882.00	07/08/2001	832.00	31/10/2001	740.00	24/01/2002	780.00
15/05/2001	874.50	08/08/2001	833.00	01/11/2001	755.00	25/01/2002	797.00
16/05/2001	878.00	09/08/2001	818.00	02/11/2001	758.00	28/01/2002	799.00
17/05/2001	880.00	10/08/2001	822.00	05/11/2001	769.00	29/01/2002	808.00
18/05/2001	882.00	13/08/2001	824.50	06/11/2001	780.50	30/01/2002	785.00
21/05/2001	876.00	14/08/2001	829.50	07/11/2001	779.50	31/01/2002	789.50
22/05/2001	888.50	15/08/2001	844.00	08/11/2001	784.00	01/02/2002	797.00
23/05/2001	895.00	16/08/2001	835.56	09/11/2001	797.00	04/02/2002	790.00
24/05/2001	893.00	17/08/2001	837.00	12/11/2001	789.00	05/02/2002	782.00
25/05/2001	909.00	20/08/2001	819.00	13/11/2001	786.50	06/02/2002	772.00
28/05/2001	896.00	21/08/2001	824.30	14/11/2001	807.50	07/02/2002	765.00
29/05/2001	892.50	22/08/2001	810.00	15/11/2001	811.50	08/02/2002	779.00
30/05/2001	882.50	23/08/2001	828.48	16/11/2001	829.50	11/02/2002	800.00
31/05/2001	878.50	24/08/2001	815.28	19/11/2001	844.00	12/02/2002	801.50
01/06/2001	880.00	27/08/2001	830.00	20/11/2001	842.00	13/02/2002	783.00
04/06/2001	878.50	28/08/2001	824.00	21/11/2001	837.00	14/02/2002	781.00
05/06/2001	882.00	29/08/2001	820.00	22/11/2001	852.50	15/02/2002	804.00
06/06/2001	894.00	30/08/2001	829.00	23/11/2001	860.00	18/02/2002	787.50
07/06/2001	900.00	31/08/2001	815.00	26/11/2001	852.00	19/02/2002	787.00
08/06/2001	916.50	03/09/2001	804.50	27/11/2001	859.00	20/02/2002	773.00
11/06/2001	908.00	04/09/2001	814.00	28/11/2001	847.00	21/02/2002	785.00
12/06/2001	895.00	05/09/2001	810.00	29/11/2001	835.00	22/02/2002	769.50
13/06/2001	878.00	06/09/2001	806.00	30/11/2001	847.50	25/02/2002	766.50
14/06/2001	858.00	07/09/2001	783.50	03/12/2001	836.00	26/02/2002	782.00
15/06/2001	841.00	10/09/2001	758.00	04/12/2001	845.00	27/02/2002	782.00
18/06/2001	839.50	11/09/2001	761.00	05/12/2001	860.00	28/02/2002	790.00
19/06/2001	854.50	12/09/2001	690.00	06/12/2001	875.00	01/03/2002	777.00
20/06/2001	854.00	13/09/2001	695.75	07/12/2001	888.00	04/03/2002	765.50
21/06/2001	864.50	14/09/2001	697.66	10/12/2001	870.50	05/03/2002	829.00
22/06/2001	845.00	17/09/2001	660.00	11/12/2001	854.00	06/03/2002	815.00
25/06/2001	846.00	18/09/2001	663.00	12/12/2001	849.00	07/03/2002	829.00
26/06/2001	846.00	19/09/2001	674.00	13/12/2001	834.50	08/03/2002	831.00
27/06/2001	826.50	20/09/2001	651.00	14/12/2001	826.00	11/03/2002	837.50
28/06/2001	825.50	21/09/2001	608.00	17/12/2001	824.00	12/03/2002	834.00
29/06/2001	840.00	24/09/2001	616.75	18/12/2001	832.00	13/03/2002	833.00
02/07/2001	843.00	25/09/2001	634.00	19/12/2001	832.00	14/03/2002	833.00
03/07/2001	846.00	26/09/2001	656.00	20/12/2001	818.00	15/03/2002	827.00
04/07/2001	843.67	27/09/2001	662.50	21/12/2001	794.00	18/03/2002	841.50
05/07/2001	839.00	28/09/2001	688.75	24/12/2001	810.50	19/03/2002	845.00
06/07/2001	831.00	01/10/2001	715.00	25/12/2001	808.00	20/03/2002	819.00
09/07/2001	819.00	02/10/2001	705.00	26/12/2001	808.00	21/03/2002	802.00
10/07/2001	809.00	03/10/2001	705.00	27/12/2001	811.00	22/03/2002	803.50
11/07/2001	796.00	04/10/2001	734.00	28/12/2001	811.00	25/03/2002	812.50
12/07/2001	793.00	05/10/2001	733.00	31/12/2001	814.00	26/03/2002	798.00
13/07/2001	801.00	08/10/2001	724.00	01/01/2002	806.00	27/03/2002	803.00
16/07/2001	809.00	09/10/2001	737.50	02/01/2002	795.00	28/03/2002	800.50
17/07/2001	797.00	10/10/2001	727.00	03/01/2002	816.50	29/03/2002	798.00

01/04/2002	798.00	25/06/2002	752.50	18/09/2002	708.00	12/12/2002	725.00
02/04/2002	798.00	26/06/2002	735.00	19/09/2002	701.00	13/12/2002	716.00
03/04/2002	794.00	27/06/2002	746.00	20/09/2002	688.50	16/12/2002	698.00
04/04/2002	795.00	28/06/2002	748.50	23/09/2002	696.00	17/12/2002	712.50
05/04/2002	788.50	01/07/2002	750.00	24/09/2002	685.00	18/12/2002	703.50
08/04/2002	790.00	02/07/2002	749.00	25/09/2002	662.00	19/12/2002	697.00
09/04/2002	791.00	03/07/2002	748.50	26/09/2002	671.00	20/12/2002	697.00
10/04/2002	785.50	04/07/2002	748.00	27/09/2002	675.00	23/12/2002	698.50
11/04/2002	793.50	05/07/2002	760.00	30/09/2002	662.50	24/12/2002	699.50
12/04/2002	786.50	08/07/2002	756.50	01/10/2002	648.50	25/12/2002	700.50
15/04/2002	783.50	09/07/2002	760.00	02/10/2002	662.00	26/12/2002	700.50
16/04/2002	788.00	10/07/2002	749.00	03/10/2002	650.00	27/12/2002	695.00
17/04/2002	798.00	11/07/2002	735.00	04/10/2002	653.50	30/12/2002	681.50
18/04/2002	808.00	12/07/2002	736.00	07/10/2002	640.00	31/12/2002	686.00
19/04/2002	806.50	15/07/2002	723.50	08/10/2002	648.00	01/01/2003	686.50
22/04/2002	806.00	16/07/2002	708.00	09/10/2002	655.00	02/01/2003	687.00
23/04/2002	808.50	17/07/2002	691.00	10/10/2002	649.50	03/01/2003	707.00
24/04/2002	807.50	18/07/2002	717.50	11/10/2002	668.00	06/01/2003	705.00
25/04/2002	815.00	19/07/2002	714.00	14/10/2002	695.00	07/01/2003	706.00
26/04/2002	818.00	22/07/2002	703.00	15/10/2002	698.00	08/01/2003	706.00
29/04/2002	812.00	23/07/2002	703.00	16/10/2002	708.00	09/01/2003	703.00
30/04/2002	811.00	24/07/2002	691.00	17/10/2002	710.50	10/01/2003	705.00
01/05/2002	815.00	25/07/2002	690.00	18/10/2002	724.00	13/01/2003	705.75
02/05/2002	817.50	26/07/2002	688.00	21/10/2002	714.50	14/01/2003	706.00
03/05/2002	825.00	29/07/2002	711.00	22/10/2002	720.00	15/01/2003	708.00
06/05/2002	837.00	30/07/2002	731.50	23/10/2002	726.00	16/01/2003	703.00
07/05/2002	831.00	31/07/2002	721.00	24/10/2002	718.00	17/01/2003	694.00
08/05/2002	842.00	01/08/2002	727.50	25/10/2002	710.00	20/01/2003	694.50
09/05/2002	845.50	02/08/2002	700.50	28/10/2002	720.00	21/01/2003	696.00
10/05/2002	835.00	05/08/2002	703.00	29/10/2002	708.50	22/01/2003	684.00
13/05/2002	840.00	06/08/2002	698.50	30/10/2002	704.50	23/01/2003	676.50
14/05/2002	860.00	07/08/2002	730.00	31/10/2002	701.50	24/01/2003	664.00
15/05/2002	867.50	08/08/2002	725.50	01/11/2002	705.50	27/01/2003	655.00
16/05/2002	861.00	09/08/2002	746.50	04/11/2002	716.00	28/01/2003	650.00
17/05/2002	856.50	12/08/2002	745.00	05/11/2002	722.00	29/01/2003	638.00
20/05/2002	868.00	13/08/2002	748.00	06/11/2002	738.00	30/01/2003	639.00
21/05/2002	847.00	14/08/2002	733.00	07/11/2002	730.00	31/01/2003	630.00
22/05/2002	849.00	15/08/2002	750.00	08/11/2002	716.50	03/02/2003	650.00
23/05/2002	844.50	16/08/2002	755.00	11/11/2002	700.00	04/02/2003	645.00
24/05/2002	843.50	19/08/2002	751.00	12/11/2002	700.50	05/02/2003	636.50
27/05/2002	838.00	20/08/2002	769.50	13/11/2002	706.00	06/02/2003	638.00
28/05/2002	844.00	21/08/2002	755.00	14/11/2002	708.50	07/02/2003	646.50
29/05/2002	833.00	22/08/2002	759.50	15/11/2002	726.00	10/02/2003	649.00
30/05/2002	829.00	23/08/2002	763.00	18/11/2002	730.00	11/02/2003	646.50
31/05/2002	822.00	26/08/2002	747.50	19/11/2002	730.00	12/02/2003	653.00
03/06/2002	830.50	27/08/2002	744.50	20/11/2002	729.00	13/02/2003	650.00
04/06/2002	834.75	28/08/2002	739.50	21/11/2002	738.00	14/02/2003	659.00
05/06/2002	839.00	29/08/2002	735.00	22/11/2002	739.50	17/02/2003	672.00
06/06/2002	844.00	30/08/2002	735.50	25/11/2002	738.00	18/02/2003	675.00
07/06/2002	827.00	02/09/2002	729.00	26/11/2002	736.00	19/02/2003	679.00
10/06/2002	814.00	03/09/2002	714.50	27/11/2002	731.50	20/02/2003	681.00
11/06/2002	820.00	04/09/2002	698.50	28/11/2002	754.50	21/02/2003	678.00
12/06/2002	814.50	05/09/2002	699.50	29/11/2002	759.50	24/02/2003	683.50
13/06/2002	806.00	06/09/2002	709.00	02/12/2002	763.00	25/02/2003	675.00
14/06/2002	788.00	09/09/2002	702.00	03/12/2002	757.50	26/02/2003	676.00
17/06/2002	772.00	10/09/2002	706.50	04/12/2002	736.50	27/02/2003	675.00
18/06/2002	792.00	11/09/2002	719.00	05/12/2002	739.00	28/02/2003	677.00
19/06/2002	774.50	12/09/2002	719.00	06/12/2002	732.00	03/03/2003	689.00
20/06/2002	769.50	13/09/2002	704.50	09/12/2002	728.00	04/03/2003	683.00
21/06/2002	754.00	16/09/2002	704.50	10/12/2002	716.50	05/03/2003	670.50
24/06/2002	764.50	17/09/2002	728.50	11/12/2002	723.00	06/03/2003	665.50

07/03/2003	658.50	02/06/2003	732.00	26/08/2003	812.50	19/11/2003	881.00
10/03/2003	664.00	03/06/2003	727.50	27/08/2003	810.00	20/11/2003	878.00
11/03/2003	655.50	04/06/2003	735.00	28/08/2003	812.50	21/11/2003	866.00
12/03/2003	656.00	05/06/2003	736.50	29/08/2003	821.50	24/11/2003	880.00
13/03/2003	649.50	06/06/2003	727.50	01/09/2003	818.50	25/11/2003	896.50
14/03/2003	668.00	09/06/2003	731.50	02/09/2003	820.00	26/11/2003	893.50
17/03/2003	665.00	10/06/2003	730.00	03/09/2003	827.00	27/11/2003	885.00
18/03/2003	690.00	11/06/2003	725.00	04/09/2003	827.00	28/11/2003	885.50
19/03/2003	678.50	12/06/2003	725.50	05/09/2003	817.00	01/12/2003	890.00
20/03/2003	683.00	13/06/2003	730.50	08/09/2003	820.00	02/12/2003	892.50
21/03/2003	687.00	16/06/2003	730.00	09/09/2003	825.50	03/12/2003	882.50
24/03/2003	676.50	17/06/2003	739.00	10/09/2003	811.50	04/12/2003	882.00
25/03/2003	670.00	18/06/2003	741.50	11/09/2003	806.50	05/12/2003	880.00
26/03/2003	671.00	19/06/2003	742.00	12/09/2003	813.50	08/12/2003	871.00
27/03/2003	667.00	20/06/2003	736.50	15/09/2003	805.00	09/12/2003	877.50
28/03/2003	670.00	23/06/2003	732.50	16/09/2003	804.50	10/12/2003	876.00
31/03/2003	651.00	24/06/2003	722.00	17/09/2003	822.00	11/12/2003	872.63
01/04/2003	651.00	25/06/2003	728.50	18/09/2003	815.00	12/12/2003	873.26
02/04/2003	674.00	26/06/2003	717.00	19/09/2003	820.50	15/12/2003	886.50
03/04/2003	673.50	27/06/2003	722.50	22/09/2003	802.00	16/12/2003	866.50
04/04/2003	675.00	30/06/2003	719.50	23/09/2003	810.00	17/12/2003	866.92
07/04/2003	691.00	01/07/2003	714.50	24/09/2003	815.00	18/12/2003	863.00
08/04/2003	689.00	02/07/2003	709.00	25/09/2003	817.00	19/12/2003	868.17
09/04/2003	682.00	03/07/2003	711.00	26/09/2003	812.00	22/12/2003	880.00
10/04/2003	679.00	04/07/2003	707.00	29/09/2003	804.50	23/12/2003	885.00
11/04/2003	675.00	07/07/2003	717.00	30/09/2003	808.50	24/12/2003	881.50
14/04/2003	671.00	08/07/2003	737.00	01/10/2003	796.50	25/12/2003	880.00
15/04/2003	678.00	09/07/2003	742.00	02/10/2003	817.50	26/12/2003	880.00
16/04/2003	685.50	10/07/2003	737.00	03/10/2003	827.50	29/12/2003	880.00
17/04/2003	676.50	11/07/2003	732.00	06/10/2003	844.50	30/12/2003	883.00
18/04/2003	683.00	14/07/2003	742.50	07/10/2003	840.00	31/12/2003	884.00
21/04/2003	683.00	15/07/2003	753.50	08/10/2003	852.00	01/01/2004	878.00
22/04/2003	682.00	16/07/2003	767.50	09/10/2003	843.50	02/01/2004	890.00
23/04/2003	684.00	17/07/2003	757.50	10/10/2003	852.50	05/01/2004	886.70
24/04/2003	669.00	18/07/2003	758.50	13/10/2003	850.50	06/01/2004	879.75
25/04/2003	657.50	21/07/2003	767.00	14/10/2003	854.00	07/01/2004	889.00
28/04/2003	651.00	22/07/2003	755.00	15/10/2003	851.50	08/01/2004	892.51
29/04/2003	677.50	23/07/2003	756.50	16/10/2003	860.00	09/01/2004	890.50
30/04/2003	682.00	24/07/2003	751.00	17/10/2003	856.00	12/01/2004	869.00
01/05/2003	685.50	25/07/2003	748.00	20/10/2003	851.50	13/01/2004	863.67
02/05/2003	679.00	28/07/2003	756.00	21/10/2003	872.00	14/01/2004	861.00
05/05/2003	691.00	29/07/2003	755.00	22/10/2003	877.50	15/01/2004	864.00
06/05/2003	697.00	30/07/2003	754.00	23/10/2003	846.50	16/01/2004	855.50
07/05/2003	693.50	31/07/2003	762.50	24/10/2003	838.00	19/01/2004	870.00
08/05/2003	712.50	01/08/2003	773.00	27/10/2003	842.50	20/01/2004	872.00
09/05/2003	708.00	04/08/2003	781.00	28/10/2003	859.00	21/01/2004	870.71
12/05/2003	714.50	05/08/2003	775.00	29/10/2003	869.00	22/01/2004	870.78
13/05/2003	708.00	06/08/2003	764.00	30/10/2003	876.50	23/01/2004	863.50
14/05/2003	706.50	07/08/2003	769.50	31/10/2003	888.00	26/01/2004	869.50
15/05/2003	712.50	08/08/2003	764.50	03/11/2003	899.50	27/01/2004	864.00
16/05/2003	715.50	11/08/2003	778.50	04/11/2003	917.50	28/01/2004	853.50
19/05/2003	709.00	12/08/2003	775.00	05/11/2003	901.00	29/01/2004	855.50
20/05/2003	696.50	13/08/2003	795.00	06/11/2003	888.00	30/01/2004	854.16
21/05/2003	698.50	14/08/2003	798.00	07/11/2003	896.00	02/02/2004	836.54
22/05/2003	701.00	15/08/2003	812.50	10/11/2003	907.00	03/02/2004	836.00
23/05/2003	708.00	18/08/2003	817.00	11/11/2003	899.00	04/02/2004	835.50
26/05/2003	711.00	19/08/2003	822.00	12/11/2003	899.50	05/02/2004	837.00
27/05/2003	711.50	20/08/2003	803.50	13/11/2003	910.00	06/02/2004	854.28
28/05/2003	721.00	21/08/2003	806.50	14/11/2003	910.00	09/02/2004	855.00
29/05/2003	729.50	22/08/2003	810.50	17/11/2003	895.00	10/02/2004	859.00
30/05/2003	725.00	25/08/2003	813.00	18/11/2003	893.00	11/02/2004	856.50

12/02/2004	856.50	07/05/2004	815.50	02/08/2004	806.50	26/10/2004	873.00
13/02/2004	853.00	10/05/2004	805.00	03/08/2004	830.50	27/10/2004	877.50
16/02/2004	861.00	11/05/2004	802.50	04/08/2004	827.00	28/10/2004	887.50
17/02/2004	860.50	12/05/2004	814.00	05/08/2004	833.00	29/10/2004	884.00
18/02/2004	862.50	13/05/2004	805.50	06/08/2004	832.50	01/11/2004	881.50
19/02/2004	862.00	14/05/2004	808.50	09/08/2004	826.00	02/11/2004	896.00
20/02/2004	868.50	17/05/2004	798.50	10/08/2004	824.00	03/11/2004	901.00
23/02/2004	873.00	18/05/2004	800.00	11/08/2004	830.00	04/11/2004	903.00
24/02/2004	878.00	19/05/2004	795.00	12/08/2004	826.00	05/11/2004	910.00
25/02/2004	863.50	20/05/2004	798.00	13/08/2004	828.00	08/11/2004	918.50
26/02/2004	866.00	21/05/2004	793.00	16/08/2004	818.50	09/11/2004	914.00
27/02/2004	880.00	24/05/2004	795.00	17/08/2004	823.50	10/11/2004	918.00
01/03/2004	870.00	25/05/2004	790.00	18/08/2004	820.00	11/11/2004	926.00
02/03/2004	868.00	26/05/2004	795.50	19/08/2004	825.00	12/11/2004	942.00
03/03/2004	855.00	27/05/2004	792.00	20/08/2004	824.50	15/11/2004	946.50
04/03/2004	851.00	28/05/2004	808.00	23/08/2004	833.00	16/11/2004	934.00
05/03/2004	855.00	31/05/2004	809.00	24/08/2004	839.00	17/11/2004	928.00
08/03/2004	852.50	01/06/2004	814.50	25/08/2004	855.50	18/11/2004	916.00
09/03/2004	845.50	02/06/2004	819.00	26/08/2004	857.50	19/11/2004	916.50
10/03/2004	849.00	03/06/2004	813.00	27/08/2004	861.50	22/11/2004	911.00
11/03/2004	850.00	04/06/2004	813.50	30/08/2004	865.50	23/11/2004	925.00
12/03/2004	842.50	07/06/2004	821.00	31/08/2004	864.00	24/11/2004	909.50
15/03/2004	849.00	08/06/2004	826.50	01/09/2004	871.00	25/11/2004	894.50
16/03/2004	844.00	09/06/2004	829.50	02/09/2004	873.50	26/11/2004	889.00
17/03/2004	841.00	10/06/2004	826.00	03/09/2004	874.50	29/11/2004	895.00
18/03/2004	833.00	11/06/2004	828.50	06/09/2004	885.00	30/11/2004	903.00
19/03/2004	824.50	14/06/2004	826.50	07/09/2004	883.50	01/12/2004	890.00
22/03/2004	813.50	15/06/2004	815.50	08/09/2004	882.00	02/12/2004	891.50
23/03/2004	807.00	16/06/2004	814.00	09/09/2004	877.00	03/12/2004	893.00
24/03/2004	807.00	17/06/2004	814.00	10/09/2004	875.50	06/12/2004	885.00
25/03/2004	808.00	18/06/2004	806.00	13/09/2004	879.50	07/12/2004	884.50
26/03/2004	822.50	21/06/2004	805.00	14/09/2004	881.00	08/12/2004	878.00
29/03/2004	814.50	22/06/2004	802.50	15/09/2004	878.50	09/12/2004	884.00
30/03/2004	820.00	23/06/2004	801.00	16/09/2004	887.00	10/12/2004	879.50
31/03/2004	817.50	24/06/2004	816.00	17/09/2004	883.50	13/12/2004	874.00
01/04/2004	810.50	25/06/2004	816.00	20/09/2004	885.00	14/12/2004	877.50
02/04/2004	814.50	28/06/2004	818.50	21/09/2004	887.00	15/12/2004	873.00
05/04/2004	822.50	29/06/2004	816.50	22/09/2004	883.00	16/12/2004	870.00
06/04/2004	827.50	30/06/2004	831.00	23/09/2004	881.00	17/12/2004	866.50
07/04/2004	827.00	01/07/2004	822.00	24/09/2004	881.00	20/12/2004	866.00
08/04/2004	822.00	02/07/2004	815.00	27/09/2004	875.50	21/12/2004	874.50
09/04/2004	820.00	05/07/2004	808.00	28/09/2004	870.00	22/12/2004	878.50
12/04/2004	820.00	06/07/2004	814.00	29/09/2004	873.00	23/12/2004	884.00
13/04/2004	829.00	07/07/2004	804.50	30/09/2004	881.00	24/12/2004	882.00
14/04/2004	827.00	08/07/2004	799.50	01/10/2004	880.50	27/12/2004	884.50
15/04/2004	827.00	09/07/2004	797.00	04/10/2004	895.50	28/12/2004	884.50
16/04/2004	823.00	12/07/2004	796.50	05/10/2004	901.00	29/12/2004	881.00
19/04/2004	819.00	13/07/2004	800.00	06/10/2004	904.00	30/12/2004	886.00
20/04/2004	821.00	14/07/2004	794.50	07/10/2004	903.00	31/12/2004	887.00
21/04/2004	825.00	15/07/2004	794.50	08/10/2004	903.00	03/01/2005	879.00
22/04/2004	830.00	16/07/2004	791.00	11/10/2004	901.50	04/01/2005	885.00
23/04/2004	836.00	19/07/2004	789.00	12/10/2004	900.00	05/01/2005	893.00
26/04/2004	830.50	20/07/2004	786.00	13/10/2004	896.50	06/01/2005	891.00
27/04/2004	830.50	21/07/2004	803.00	14/10/2004	887.50	07/01/2005	885.00
28/04/2004	832.00	22/07/2004	805.50	15/10/2004	891.00	10/01/2005	883.00
29/04/2004	828.00	23/07/2004	802.00	18/10/2004	889.00	11/01/2005	879.50
30/04/2004	821.00	26/07/2004	801.00	19/10/2004	898.50	12/01/2005	875.00
03/05/2004	808.00	27/07/2004	800.00	20/10/2004	893.00	13/01/2005	871.00
04/05/2004	819.50	28/07/2004	811.00	21/10/2004	887.50	14/01/2005	869.00
05/05/2004	816.50	29/07/2004	805.00	22/10/2004	881.50	17/01/2005	878.50
06/05/2004	825.00	30/07/2004	812.00	25/10/2004	871.50	18/01/2005	881.00

19/01/2005	882.00	14/04/2005	842.00	08/07/2005	908.00	03/10/2005	921.00
20/01/2005	872.00	15/04/2005	841.00	11/07/2005	914.50	04/10/2005	924.50
21/01/2005	874.50	18/04/2005	828.00	12/07/2005	906.00	05/10/2005	916.50
24/01/2005	865.00	19/04/2005	829.50	13/07/2005	903.50	06/10/2005	900.00
25/01/2005	870.00	20/04/2005	827.00	14/07/2005	916.00	07/10/2005	899.00
26/01/2005	877.50	21/04/2005	823.50	15/07/2005	916.50	10/10/2005	904.50
27/01/2005	885.00	22/04/2005	832.50	18/07/2005	918.50	11/10/2005	905.00
28/01/2005	876.00	25/04/2005	830.50	19/07/2005	921.50	12/10/2005	903.50
31/01/2005	874.50	26/04/2005	839.00	20/07/2005	923.00	13/10/2005	902.00
01/02/2005	875.00	27/04/2005	838.50	21/07/2005	928.00	14/10/2005	894.00
02/02/2005	877.50	28/04/2005	839.50	22/07/2005	926.50	17/10/2005	890.00
03/02/2005	873.00	29/04/2005	832.00	25/07/2005	938.00	18/10/2005	895.00
04/02/2005	876.00	02/05/2005	835.50	26/07/2005	935.00	19/10/2005	886.00
07/02/2005	892.00	03/05/2005	843.00	27/07/2005	936.50	20/10/2005	884.00
08/02/2005	903.00	04/05/2005	848.50	28/07/2005	930.00	21/10/2005	876.50
09/02/2005	904.00	05/05/2005	852.50	29/07/2005	925.00	24/10/2005	880.50
10/02/2005	906.00	06/05/2005	854.00	01/08/2005	926.00	25/10/2005	883.00
11/02/2005	903.00	09/05/2005	859.00	02/08/2005	932.00	26/10/2005	875.50
14/02/2005	904.50	10/05/2005	862.00	03/08/2005	929.00	27/10/2005	881.00
15/02/2005	902.50	11/05/2005	854.50	04/08/2005	930.00	28/10/2005	871.50
16/02/2005	904.50	12/05/2005	861.50	05/08/2005	921.50	31/10/2005	878.00
17/02/2005	904.50	13/05/2005	859.50	08/08/2005	928.00	01/11/2005	888.50
18/02/2005	900.00	16/05/2005	863.00	09/08/2005	920.00	02/11/2005	893.50
21/02/2005	900.00	17/05/2005	866.50	10/08/2005	919.50	03/11/2005	890.00
22/02/2005	893.00	18/05/2005	863.50	11/08/2005	920.00	04/11/2005	893.50
23/02/2005	886.00	19/05/2005	864.00	12/08/2005	921.00	07/11/2005	901.00
24/02/2005	887.00	20/05/2005	864.00	15/08/2005	915.00	08/11/2005	912.00
25/02/2005	888.00	23/05/2005	867.50	16/08/2005	917.00	09/11/2005	913.00
28/02/2005	886.00	24/05/2005	866.00	17/08/2005	907.50	10/11/2005	915.50
01/03/2005	868.00	25/05/2005	866.50	18/08/2005	911.00	11/11/2005	922.50
02/03/2005	860.00	26/05/2005	865.00	19/08/2005	907.00	14/11/2005	922.50
03/03/2005	858.50	27/05/2005	870.50	22/08/2005	906.50	15/11/2005	923.00
04/03/2005	860.00	30/05/2005	868.00	23/08/2005	904.50	16/11/2005	928.50
07/03/2005	858.50	31/05/2005	873.00	24/08/2005	898.50	17/11/2005	934.50
08/03/2005	858.00	01/06/2005	870.50	25/08/2005	888.50	18/11/2005	942.00
09/03/2005	858.50	02/06/2005	874.00	26/08/2005	889.50	21/11/2005	947.00
10/03/2005	849.50	03/06/2005	873.25	29/08/2005	887.50	22/11/2005	947.00
11/03/2005	851.00	06/06/2005	872.50	30/08/2005	891.00	23/11/2005	944.00
14/03/2005	850.00	07/06/2005	869.00	31/08/2005	893.00	24/11/2005	944.00
15/03/2005	852.00	08/06/2005	869.50	01/09/2005	895.00	25/11/2005	938.50
16/03/2005	842.00	09/06/2005	874.00	02/09/2005	885.50	28/11/2005	944.00
17/03/2005	835.50	10/06/2005	879.00	05/09/2005	883.00	29/11/2005	937.00
18/03/2005	836.00	13/06/2005	882.00	06/09/2005	883.00	30/11/2005	932.00
21/03/2005	839.50	14/06/2005	884.00	07/09/2005	886.00	01/12/2005	930.50
22/03/2005	842.50	15/06/2005	884.50	08/09/2005	891.00	02/12/2005	936.50
23/03/2005	838.00	16/06/2005	879.50	09/09/2005	887.50	05/12/2005	936.50
24/03/2005	846.00	17/06/2005	877.00	12/09/2005	891.50	06/12/2005	925.50
25/03/2005	844.50	20/06/2005	879.00	13/09/2005	893.50	07/12/2005	927.00
28/03/2005	844.50	21/06/2005	879.00	14/09/2005	894.00	08/12/2005	923.00
29/03/2005	841.50	22/06/2005	883.50	15/09/2005	894.00	09/12/2005	917.00
30/03/2005	836.00	23/06/2005	892.50	16/09/2005	894.50	12/12/2005	914.00
31/03/2005	843.00	24/06/2005	891.50	19/09/2005	897.00	13/12/2005	908.50
01/04/2005	837.00	27/06/2005	888.50	20/09/2005	898.00	14/12/2005	912.50
04/04/2005	836.50	28/06/2005	888.00	21/09/2005	895.00	15/12/2005	919.00
05/04/2005	835.00	29/06/2005	894.50	22/09/2005	889.00	16/12/2005	920.00
06/04/2005	837.00	30/06/2005	889.00	23/09/2005	898.50	19/12/2005	924.00
07/04/2005	837.50	01/07/2005	893.00	26/09/2005	909.50	20/12/2005	921.50
08/04/2005	847.00	04/07/2005	902.00	27/09/2005	914.50	21/12/2005	930.00
11/04/2005	843.50	05/07/2005	904.50	28/09/2005	912.00	22/12/2005	932.50
12/04/2005	838.00	06/07/2005	910.00	29/09/2005	918.00	23/12/2005	933.00
13/04/2005	842.50	07/07/2005	908.00	30/09/2005	925.00	26/12/2005	935.50

27/12/2005	935.50	22/03/2006	967.50	15/06/2006	933.00	08/09/2006	952.50
28/12/2005	931.50	23/03/2006	970.00	16/06/2006	944.00	11/09/2006	950.50
29/12/2005	937.00	24/03/2006	968.50	19/06/2006	947.00	12/09/2006	956.50
30/12/2005	935.00	27/03/2006	966.50	20/06/2006	935.50	13/09/2006	961.00
02/01/2006	933.00	28/03/2006	958.00	21/06/2006	935.50	14/09/2006	960.00
03/01/2006	935.00	29/03/2006	956.50	22/06/2006	942.00	15/09/2006	953.00
04/01/2006	935.00	30/03/2006	961.00	23/06/2006	944.50	18/09/2006	956.00
05/01/2006	934.00	31/03/2006	962.00	26/06/2006	948.50	19/09/2006	958.50
06/01/2006	941.50	03/04/2006	977.00	27/06/2006	945.50	20/09/2006	955.00
09/01/2006	952.00	04/04/2006	973.00	28/06/2006	938.00	21/09/2006	960.00
10/01/2006	961.00	05/04/2006	969.50	29/06/2006	947.00	22/09/2006	957.00
11/01/2006	963.00	06/04/2006	973.50	30/06/2006	959.00	25/09/2006	954.00
12/01/2006	959.50	07/04/2006	972.50	03/07/2006	954.00	26/09/2006	954.50
13/01/2006	958.50	10/04/2006	970.00	04/07/2006	952.00	27/09/2006	961.50
16/01/2006	952.50	11/04/2006	970.50	05/07/2006	950.00	28/09/2006	967.50
17/01/2006	951.00	12/04/2006	964.00	06/07/2006	951.00	29/09/2006	972.50
18/01/2006	941.00	13/04/2006	962.50	07/07/2006	963.00	02/10/2006	975.50
19/01/2006	953.00	14/04/2006	966.50	10/07/2006	967.00	03/10/2006	965.00
20/01/2006	953.50	17/04/2006	966.50	11/07/2006	966.00	04/10/2006	967.00
23/01/2006	933.50	18/04/2006	963.00	12/07/2006	965.50	05/10/2006	983.00
24/01/2006	930.50	19/04/2006	965.00	13/07/2006	961.00	06/10/2006	1000.00
25/01/2006	929.00	20/04/2006	967.50	14/07/2006	943.50	09/10/2006	995.00
26/01/2006	930.50	21/04/2006	970.00	17/07/2006	942.50	10/10/2006	1002.50
27/01/2006	938.00	24/04/2006	958.50	18/07/2006	948.50	11/10/2006	1010.00
30/01/2006	940.00	25/04/2006	953.50	19/07/2006	953.50	12/10/2006	1010.00
31/01/2006	933.50	26/04/2006	953.00	20/07/2006	965.00	13/10/2006	1013.50
01/02/2006	931.50	27/04/2006	955.50	21/07/2006	955.00	16/10/2006	1014.00
02/02/2006	939.50	28/04/2006	946.00	24/07/2006	949.50	17/10/2006	1013.00
03/02/2006	930.50	01/05/2006	947.50	25/07/2006	969.50	18/10/2006	1008.00
06/02/2006	942.00	02/05/2006	953.00	26/07/2006	967.00	19/10/2006	1008.00
07/02/2006	942.00	03/05/2006	967.00	27/07/2006	970.50	20/10/2006	1006.00
08/02/2006	943.00	04/05/2006	960.00	28/07/2006	973.00	23/10/2006	1006.00
09/02/2006	947.00	05/05/2006	963.50	31/07/2006	973.00	24/10/2006	1009.50
10/02/2006	948.50	08/05/2006	970.50	01/08/2006	970.00	25/10/2006	1004.50
13/02/2006	945.50	09/05/2006	976.00	02/08/2006	964.00	26/10/2006	1007.50
14/02/2006	950.00	10/05/2006	982.00	03/08/2006	960.50	27/10/2006	1004.00
15/02/2006	955.50	11/05/2006	987.00	04/08/2006	957.00	30/10/2006	994.50
16/02/2006	956.50	12/05/2006	966.00	07/08/2006	950.00	31/10/2006	992.00
17/02/2006	962.00	15/05/2006	945.50	08/08/2006	953.50	01/11/2006	1000.00
20/02/2006	957.00	16/05/2006	944.00	09/08/2006	953.50	02/11/2006	1012.00
21/02/2006	961.50	17/05/2006	958.00	10/08/2006	956.00	03/11/2006	1011.00
22/02/2006	956.50	18/05/2006	950.00	11/08/2006	961.00	06/11/2006	1015.00
23/02/2006	964.50	19/05/2006	941.50	14/08/2006	956.50	07/11/2006	1023.50
24/02/2006	969.50	22/05/2006	938.00	15/08/2006	959.00	08/11/2006	1018.00
27/02/2006	985.00	23/05/2006	915.00	16/08/2006	960.00	09/11/2006	1019.50
28/02/2006	993.50	24/05/2006	923.00	17/08/2006	958.00	10/11/2006	1017.00
01/03/2006	978.00	25/05/2006	926.50	18/08/2006	954.00	13/11/2006	1007.50
02/03/2006	980.00	26/05/2006	933.00	21/08/2006	949.00	14/11/2006	999.00
03/03/2006	977.00	29/05/2006	944.00	22/08/2006	947.50	15/11/2006	996.00
06/03/2006	970.00	30/05/2006	936.00	23/08/2006	947.00	16/11/2006	995.00
07/03/2006	982.00	31/05/2006	910.00	24/08/2006	944.50	17/11/2006	1001.00
08/03/2006	984.00	01/06/2006	929.50	25/08/2006	942.50	20/11/2006	984.00
09/03/2006	988.00	02/06/2006	933.00	28/08/2006	949.00	21/11/2006	989.50
10/03/2006	985.00	05/06/2006	928.00	29/08/2006	954.00	22/11/2006	983.00
13/03/2006	994.00	06/06/2006	921.50	30/08/2006	952.00	23/11/2006	983.00
14/03/2006	988.00	07/06/2006	928.00	31/08/2006	952.50	24/11/2006	976.00
15/03/2006	987.50	08/06/2006	923.50	01/09/2006	957.00	27/11/2006	961.00
16/03/2006	981.00	09/06/2006	935.00	04/09/2006	953.50	28/11/2006	950.00
17/03/2006	981.00	12/06/2006	934.50	05/09/2006	963.00	29/11/2006	950.00
20/03/2006	988.00	13/06/2006	925.00	06/09/2006	956.50	30/11/2006	950.00
21/03/2006	982.50	14/06/2006	924.00	07/09/2006	952.00	01/12/2006	940.50

04/12/2006	935.00	03/01/2007	942.00	02/02/2007	933.50	06/03/2007	902.00
05/12/2006	937.00	04/01/2007	946.50	05/02/2007	935.00	07/03/2007	900.50
06/12/2006	921.50	05/01/2007	945.00	06/02/2007	936.50	08/03/2007	906.50
07/12/2006	919.00	08/01/2007	940.50	07/02/2007	932.00	09/03/2007	909.50
08/12/2006	920.50	09/01/2007	933.00	08/02/2007	910.00	12/03/2007	911.50
11/12/2006	921.50	10/01/2007	922.00	09/02/2007	917.00	13/03/2007	909.00
12/12/2006	920.00	11/01/2007	921.50	12/02/2007	916.50	14/03/2007	893.00
13/12/2006	917.50	12/01/2007	922.00	13/02/2007	916.00	15/03/2007	888.00
14/12/2006	922.00	15/01/2007	919.50	14/02/2007	919.50	16/03/2007	881.50
15/12/2006	930.00	16/01/2007	918.50	15/02/2007	917.50	19/03/2007	888.00
18/12/2006	931.50	17/01/2007	916.50	16/02/2007	914.00	20/03/2007	886.00
19/12/2006	928.00	18/01/2007	915.50	19/02/2007	912.00	21/03/2007	880.00
20/12/2006	931.50	19/01/2007	924.50	20/02/2007	910.00	22/03/2007	891.00
21/12/2006	925.00	22/01/2007	940.00	21/02/2007	911.50	23/03/2007	900.00
22/12/2006	923.50	23/01/2007	932.50	22/02/2007	911.50	26/03/2007	901.00
25/12/2006	924.00	24/01/2007	932.50	23/02/2007	906.00	27/03/2007	891.50
26/12/2006	924.00	25/01/2007	938.00	26/02/2007	900.00	28/03/2007	883.00
27/12/2006	928.00	26/01/2007	933.00	27/02/2007	898.00	29/03/2007	883.50
28/12/2006	934.50	29/01/2007	930.00	28/02/2007	887.50	30/03/2007	888.00
29/12/2006	931.50	30/01/2007	935.00	01/03/2007	891.00		
01/01/2007	931.00	31/01/2007	930.00	02/03/2007	888.00		
02/01/2007	933.50	01/02/2007	933.00	05/03/2007	879.00		

Appendix C.2: *The historic open share prices of Lloyds TSB Bank covers the period from 3rd July 2000 until 30th March 2007.*

Date	Prices
03/07/2000	618.50
04/07/2000	604.50
05/07/2000	590.00
06/07/2000	589.00
07/07/2000	586.50
10/07/2000	584.00
11/07/2000	576.50
12/07/2000	576.50
13/07/2000	587.00
14/07/2000	610.50
17/07/2000	620.50
18/07/2000	611.50
19/07/2000	613.00
20/07/2000	607.00
21/07/2000	620.00
24/07/2000	617.00
25/07/2000	614.00
26/07/2000	626.00
27/07/2000	607.18
28/07/2000	588.35
31/07/2000	605.00
01/08/2000	590.00
02/08/2000	560.00
03/08/2000	618.00
04/08/2000	583.00
07/08/2000	603.00
08/08/2000	592.50
09/08/2000	614.25
10/08/2000	613.50
11/08/2000	597.50
14/08/2000	587.00
15/08/2000	580.75
16/08/2000	589.00
17/08/2000	591.25
18/08/2000	597.00
21/08/2000	605.00
22/08/2000	592.00
23/08/2000	637.00
24/08/2000	637.00
25/08/2000	654.00
28/08/2000	642.50
29/08/2000	638.00
30/08/2000	657.75
31/08/2000	640.00
01/09/2000	651.00
04/09/2000	627.00
05/09/2000	650.00
06/09/2000	653.50
07/09/2000	640.00
08/09/2000	649.50
11/09/2000	634.00
12/09/2000	628.00
13/09/2000	613.00
14/09/2000	619.50
15/09/2000	630.00
18/09/2000	604.00
19/09/2000	600.00
20/09/2000	603.00
21/09/2000	590.00
22/09/2000	582.50
25/09/2000	613.50
26/09/2000	600.00
27/09/2000	601.50
28/09/2000	612.00
29/09/2000	632.50
02/10/2000	635.50
03/10/2000	647.00
04/10/2000	658.50
05/10/2000	675.00
06/10/2000	674.50
09/10/2000	670.00
10/10/2000	668.50
11/10/2000	620.00
12/10/2000	619.00
13/10/2000	620.00
16/10/2000	625.00
17/10/2000	630.00
18/10/2000	652.50
19/10/2000	625.50
20/10/2000	645.50
23/10/2000	646.00
24/10/2000	653.00
25/10/2000	646.00
26/10/2000	660.00
27/10/2000	673.00
30/10/2000	650.00
31/10/2000	678.50
01/11/2000	707.00
02/11/2000	698.00
03/11/2000	720.00
06/11/2000	715.00
07/11/2000	714.50
08/11/2000	705.00
09/11/2000	705.00
10/11/2000	719.00
13/11/2000	693.00
14/11/2000	688.50
15/11/2000	698.50
16/11/2000	687.00
17/11/2000	675.00
20/11/2000	672.00
21/11/2000	706.50
22/11/2000	650.00
23/11/2000	677.50
24/11/2000	668.00
27/11/2000	706.00
28/11/2000	705.00
29/11/2000	704.50
30/11/2000	691.00
01/12/2000	676.00
04/12/2000	696.00
05/12/2000	660.00
06/12/2000	643.00
07/12/2000	620.00
08/12/2000	642.00
11/12/2000	648.00
12/12/2000	676.00
13/12/2000	680.00
14/12/2000	698.50
15/12/2000	696.00
18/12/2000	693.00
19/12/2000	712.00
20/12/2000	725.00
21/12/2000	696.00
22/12/2000	693.00
25/12/2000	695.00
26/12/2000	695.00
27/12/2000	698.00
28/12/2000	710.50
29/12/2000	710.00
01/01/2001	708.00
02/01/2001	700.00
03/01/2001	706.75
04/01/2001	726.00
05/01/2001	743.00
08/01/2001	753.00
09/01/2001	748.50
10/01/2001	744.50
11/01/2001	725.50
12/01/2001	736.50
15/01/2001	733.75
16/01/2001	731.50
17/01/2001	727.50
18/01/2001	734.00
19/01/2001	731.00
22/01/2001	700.00
23/01/2001	715.00
24/01/2001	717.00
25/01/2001	719.00
26/01/2001	726.50
29/01/2001	734.00
30/01/2001	740.00
31/01/2001	720.00
01/02/2001	699.00
02/02/2001	687.00
05/02/2001	702.00
06/02/2001	699.00
07/02/2001	725.00
08/02/2001	706.00
09/02/2001	715.00
12/02/2001	703.50
13/02/2001	716.00
14/02/2001	719.00
15/02/2001	720.00
16/02/2001	705.00
19/02/2001	680.00
20/02/2001	674.50
21/02/2001	650.00
22/02/2001	631.25
23/02/2001	647.00
26/02/2001	635.00
27/02/2001	646.00
28/02/2001	641.00
01/03/2001	660.00
02/03/2001	675.00
05/03/2001	661.50
06/03/2001	664.00
07/03/2001	660.00
08/03/2001	670.00
09/03/2001	665.00
12/03/2001	645.00
13/03/2001	631.75
14/03/2001	638.38
15/03/2001	645.00
16/03/2001	646.00
19/03/2001	614.00
20/03/2001	624.00
21/03/2001	638.00
22/03/2001	616.75
23/03/2001	613.00
26/03/2001	641.00
27/03/2001	655.00
28/03/2001	697.00
29/03/2001	695.00
30/03/2001	675.00
02/04/2001	696.00
03/04/2001	700.00
04/04/2001	684.50
05/04/2001	700.50
06/04/2001	705.00
09/04/2001	697.50
10/04/2001	714.00
11/04/2001	720.00
12/04/2001	710.00
13/04/2001	700.50
16/04/2001	700.50
17/04/2001	708.50
18/04/2001	713.00
19/04/2001	693.00
20/04/2001	715.00
23/04/2001	710.00
24/04/2001	690.00
25/04/2001	704.00
26/04/2001	719.00
27/04/2001	733.50
30/04/2001	720.00
01/05/2001	720.00
02/05/2001	730.00
03/05/2001	742.00
04/05/2001	720.00
07/05/2001	738.50
08/05/2001	740.00
09/05/2001	725.00

10/05/2001	740.00	03/08/2001	732.00	29/10/2001	706.41	22/01/2002	721.50
11/05/2001	767.00	06/08/2001	741.00	30/10/2001	685.50	23/01/2002	728.50
14/05/2001	750.00	07/08/2001	726.66	31/10/2001	685.00	24/01/2002	743.00
15/05/2001	748.00	08/08/2001	717.00	01/11/2001	700.00	25/01/2002	757.00
16/05/2001	733.75	09/08/2001	710.00	02/11/2001	697.60	28/01/2002	759.00
17/05/2001	746.00	10/08/2001	729.00	05/11/2001	699.50	29/01/2002	767.00
18/05/2001	745.00	13/08/2001	733.00	06/11/2001	725.00	30/01/2002	753.00
21/05/2001	738.00	14/08/2001	721.50	07/11/2001	736.00	31/01/2002	751.00
22/05/2001	721.00	15/08/2001	726.50	08/11/2001	729.90	01/02/2002	763.00
23/05/2001	720.50	16/08/2001	729.33	09/11/2001	717.00	04/02/2002	738.50
24/05/2001	722.00	17/08/2001	733.00	12/11/2001	706.00	05/02/2002	731.00
25/05/2001	727.00	20/08/2001	720.00	13/11/2001	714.00	06/02/2002	737.00
28/05/2001	709.00	21/08/2001	729.50	14/11/2001	715.00	07/02/2002	722.00
29/05/2001	715.00	22/08/2001	736.00	15/11/2001	717.00	08/02/2002	751.00
30/05/2001	707.00	23/08/2001	744.00	16/11/2001	726.00	11/02/2002	744.50
31/05/2001	703.00	24/08/2001	727.96	19/11/2001	744.50	12/02/2002	758.50
01/06/2001	701.50	27/08/2001	739.00	20/11/2001	736.50	13/02/2002	754.50
04/06/2001	719.50	28/08/2001	739.00	21/11/2001	739.00	14/02/2002	763.00
05/06/2001	719.00	29/08/2001	723.00	22/11/2001	757.00	15/02/2002	763.00
06/06/2001	732.50	30/08/2001	725.50	23/11/2001	751.00	18/02/2002	727.00
07/06/2001	741.00	31/08/2001	707.25	26/11/2001	745.00	19/02/2002	736.50
08/06/2001	753.50	03/09/2001	717.50	27/11/2001	754.00	20/02/2002	736.00
11/06/2001	741.50	04/09/2001	707.00	28/11/2001	734.00	21/02/2002	735.00
12/06/2001	720.00	05/09/2001	710.00	29/11/2001	720.00	22/02/2002	736.00
13/06/2001	712.50	06/09/2001	701.00	30/11/2001	730.00	25/02/2002	746.00
14/06/2001	708.00	07/09/2001	700.00	03/12/2001	722.00	26/02/2002	749.50
15/06/2001	689.00	10/09/2001	666.00	04/12/2001	724.50	27/02/2002	723.50
18/06/2001	706.25	11/09/2001	675.00	05/12/2001	719.50	28/02/2002	714.50
19/06/2001	710.00	12/09/2001	611.00	06/12/2001	710.00	01/03/2002	683.50
20/06/2001	702.00	13/09/2001	649.61	07/12/2001	735.00	04/03/2002	715.50
21/06/2001	630.00	14/09/2001	680.00	10/12/2001	725.00	05/03/2002	723.00
22/06/2001	725.00	17/09/2001	641.64	11/12/2001	709.50	06/03/2002	711.00
25/06/2001	725.00	18/09/2001	667.00	12/12/2001	733.50	07/03/2002	718.50
26/06/2001	714.00	19/09/2001	667.00	13/12/2001	703.50	08/03/2002	715.00
27/06/2001	700.00	20/09/2001	630.00	14/12/2001	715.00	11/03/2002	724.00
28/06/2001	707.00	21/09/2001	610.00	17/12/2001	700.50	12/03/2002	715.50
29/06/2001	702.50	24/09/2001	623.00	18/12/2001	715.50	13/03/2002	710.00
02/07/2001	707.00	25/09/2001	621.50	19/12/2001	715.00	14/03/2002	736.50
03/07/2001	717.25	26/09/2001	637.50	20/12/2001	734.00	15/03/2002	728.00
04/07/2001	701.00	27/09/2001	626.50	21/12/2001	711.00	18/03/2002	745.00
05/07/2001	706.00	28/09/2001	638.25	24/12/2001	729.50	19/03/2002	737.50
06/07/2001	699.50	01/10/2001	650.00	25/12/2001	740.00	20/03/2002	738.50
09/07/2001	670.00	02/10/2001	648.40	26/12/2001	740.00	21/03/2002	731.50
10/07/2001	668.00	03/10/2001	670.00	27/12/2001	740.00	22/03/2002	722.00
11/07/2001	664.00	04/10/2001	660.00	28/12/2001	757.00	25/03/2002	727.00
12/07/2001	674.00	05/10/2001	702.00	31/12/2001	757.00	26/03/2002	712.50
13/07/2001	678.56	08/10/2001	670.50	01/01/2002	746.00	27/03/2002	699.50
16/07/2001	683.12	09/10/2001	687.00	02/01/2002	745.00	28/03/2002	713.75
17/07/2001	688.00	10/10/2001	682.00	03/01/2002	749.00	29/03/2002	711.00
18/07/2001	669.00	11/10/2001	697.00	04/01/2002	753.00	01/04/2002	711.00
19/07/2001	667.00	12/10/2001	706.00	07/01/2002	753.00	02/04/2002	728.00
20/07/2001	651.00	15/10/2001	690.00	08/01/2002	740.00	03/04/2002	710.00
23/07/2001	654.50	16/10/2001	696.50	09/01/2002	733.50	04/04/2002	711.00
24/07/2001	665.00	17/10/2001	703.00	10/01/2002	728.50	05/04/2002	717.00
25/07/2001	671.50	18/10/2001	712.00	11/01/2002	732.00	08/04/2002	715.00
26/07/2001	650.00	19/10/2001	693.00	14/01/2002	729.00	09/04/2002	715.00
27/07/2001	663.00	22/10/2001	695.00	15/01/2002	715.00	10/04/2002	714.50
30/07/2001	697.00	23/10/2001	691.50	16/01/2002	721.50	11/04/2002	735.00
31/07/2001	696.50	24/10/2001	711.50	17/01/2002	711.00	12/04/2002	729.50
01/08/2001	721.30	25/10/2001	720.00	18/01/2002	725.00	15/04/2002	743.50
02/08/2001	715.00	26/10/2001	713.21	21/01/2002	716.00	16/04/2002	743.00

17/04/2002	751.00	11/07/2002	615.00	04/10/2002	500.00	30/12/2002	439.50
18/04/2002	759.00	12/07/2002	603.00	07/10/2002	487.00	31/12/2002	436.00
19/04/2002	755.00	15/07/2002	570.00	08/10/2002	503.00	01/01/2003	446.00
22/04/2002	760.00	16/07/2002	543.00	09/10/2002	494.00	02/01/2003	453.00
23/04/2002	760.00	17/07/2002	552.00	10/10/2002	496.50	03/01/2003	459.25
24/04/2002	755.50	18/07/2002	606.00	11/10/2002	523.50	06/01/2003	451.00
25/04/2002	776.00	19/07/2002	613.50	14/10/2002	535.00	07/01/2003	425.00
26/04/2002	791.00	22/07/2002	585.00	15/10/2002	550.50	08/01/2003	429.00
29/04/2002	786.00	23/07/2002	582.50	16/10/2002	566.50	09/01/2003	429.00
30/04/2002	787.00	24/07/2002	555.00	17/10/2002	568.00	10/01/2003	444.50
01/05/2002	791.50	25/07/2002	565.00	18/10/2002	583.50	13/01/2003	446.75
02/05/2002	786.00	26/07/2002	587.00	21/10/2002	574.00	14/01/2003	445.55
03/05/2002	798.00	29/07/2002	618.00	22/10/2002	577.00	15/01/2003	438.50
06/05/2002	817.00	30/07/2002	660.00	23/10/2002	591.00	16/01/2003	436.50
07/05/2002	814.00	31/07/2002	639.00	24/10/2002	565.00	17/01/2003	425.00
08/05/2002	796.50	01/08/2002	625.00	25/10/2002	556.50	20/01/2003	426.25
09/05/2002	782.50	02/08/2002	565.00	28/10/2002	563.50	21/01/2003	419.00
10/05/2002	773.00	05/08/2002	589.00	29/10/2002	560.00	22/01/2003	393.44
13/05/2002	781.00	06/08/2002	561.00	30/10/2002	552.50	23/01/2003	404.00
14/05/2002	789.00	07/08/2002	597.00	31/10/2002	554.00	24/01/2003	401.50
15/05/2002	769.00	08/08/2002	579.50	01/11/2002	548.00	27/01/2003	388.00
16/05/2002	763.00	09/08/2002	574.00	04/11/2002	547.50	28/01/2003	379.50
17/05/2002	769.00	12/08/2002	594.00	05/11/2002	577.50	29/01/2003	376.00
20/05/2002	770.00	13/08/2002	580.00	06/11/2002	589.00	30/01/2003	377.00
21/05/2002	760.00	14/08/2002	562.00	07/11/2002	584.00	31/01/2003	375.25
22/05/2002	750.00	15/08/2002	557.00	08/11/2002	569.50	03/02/2003	402.00
23/05/2002	748.00	16/08/2002	567.50	11/11/2002	550.50	04/02/2003	398.00
24/05/2002	752.00	19/08/2002	599.00	12/11/2002	541.00	05/02/2003	396.00
27/05/2002	750.00	20/08/2002	597.00	13/11/2002	537.00	06/02/2003	402.00
28/05/2002	750.00	21/08/2002	592.00	14/11/2002	528.50	07/02/2003	401.25
29/05/2002	736.50	22/08/2002	599.00	15/11/2002	504.50	10/02/2003	407.75
30/05/2002	738.00	23/08/2002	589.00	18/11/2002	507.00	11/02/2003	402.00
31/05/2002	739.00	26/08/2002	589.00	19/11/2002	510.00	12/02/2003	418.00
03/06/2002	735.50	27/08/2002	590.00	20/11/2002	526.00	13/02/2003	408.25
04/06/2002	733.75	28/08/2002	568.00	21/11/2002	546.00	14/02/2003	446.00
05/06/2002	732.00	29/08/2002	568.00	22/11/2002	564.00	17/02/2003	411.00
06/06/2002	736.50	30/08/2002	559.00	25/11/2002	566.00	18/02/2003	405.75
07/06/2002	710.00	02/09/2002	559.00	26/11/2002	543.50	19/02/2003	412.50
10/06/2002	710.00	03/09/2002	535.50	27/11/2002	532.00	20/02/2003	398.00
11/06/2002	709.00	04/09/2002	535.00	28/11/2002	550.00	21/02/2003	392.00
12/06/2002	700.50	05/09/2002	540.00	29/11/2002	553.50	24/02/2003	397.75
13/06/2002	703.50	06/09/2002	553.00	02/12/2002	546.50	25/02/2003	385.50
14/06/2002	675.00	09/09/2002	551.50	03/12/2002	537.50	26/02/2003	368.00
17/06/2002	666.50	10/09/2002	558.00	04/12/2002	515.50	27/02/2003	350.25
18/06/2002	665.00	11/09/2002	570.00	05/12/2002	515.50	28/02/2003	340.00
19/06/2002	645.00	12/09/2002	565.00	06/12/2002	508.00	03/03/2003	354.75
20/06/2002	639.50	13/09/2002	544.00	09/12/2002	496.00	04/03/2003	352.00
21/06/2002	620.00	16/09/2002	530.50	10/12/2002	475.00	05/03/2003	335.25
24/06/2002	643.00	17/09/2002	542.00	11/12/2002	470.00	06/03/2003	335.75
25/06/2002	640.00	18/09/2002	519.00	12/12/2002	464.50	07/03/2003	320.25
26/06/2002	653.50	19/09/2002	492.50	13/12/2002	450.00	10/03/2003	311.25
27/06/2002	654.00	20/09/2002	489.00	16/12/2002	434.00	11/03/2003	300.00
28/06/2002	644.00	23/09/2002	499.00	17/12/2002	463.50	12/03/2003	313.00
01/07/2002	651.00	24/09/2002	461.00	18/12/2002	442.00	13/03/2003	303.00
02/07/2002	658.00	25/09/2002	454.00	19/12/2002	427.50	14/03/2003	329.00
03/07/2002	639.00	26/09/2002	478.00	20/12/2002	437.00	17/03/2003	358.00
04/07/2002	614.00	27/09/2002	495.00	23/12/2002	450.00	18/03/2003	354.00
05/07/2002	618.00	30/09/2002	490.00	24/12/2002	447.00	19/03/2003	360.25
08/07/2002	634.00	01/10/2002	473.00	25/12/2002	449.00	20/03/2003	359.25
09/07/2002	625.00	02/10/2002	506.00	26/12/2002	449.00	21/03/2003	354.00
10/07/2002	622.00	03/10/2002	504.00	27/12/2002	444.00	24/03/2003	365.00

25/03/2003	346.00	18/06/2003	474.50	11/09/2003	431.25	05/12/2003	416.00
26/03/2003	349.25	19/06/2003	466.00	12/09/2003	430.00	08/12/2003	411.00
27/03/2003	349.00	20/06/2003	451.00	15/09/2003	435.00	09/12/2003	413.75
28/03/2003	340.00	23/06/2003	450.75	16/09/2003	442.00	10/12/2003	410.00
31/03/2003	325.50	24/06/2003	451.00	17/09/2003	446.00	11/12/2003	404.04
01/04/2003	325.50	25/06/2003	442.00	18/09/2003	434.75	12/12/2003	405.00
02/04/2003	330.00	26/06/2003	436.00	19/09/2003	442.00	15/12/2003	410.00
03/04/2003	340.00	27/06/2003	440.50	22/09/2003	430.00	16/12/2003	415.50
04/04/2003	339.00	30/06/2003	434.25	23/09/2003	431.50	17/12/2003	424.50
07/04/2003	361.00	01/07/2003	425.00	24/09/2003	424.75	18/12/2003	425.00
08/04/2003	371.00	02/07/2003	431.50	25/09/2003	418.00	19/12/2003	434.00
09/04/2003	366.00	03/07/2003	431.00	26/09/2003	419.75	22/12/2003	435.00
10/04/2003	362.00	04/07/2003	427.25	29/09/2003	419.25	23/12/2003	441.00
11/04/2003	377.00	07/07/2003	435.00	30/09/2003	424.75	24/12/2003	443.00
14/04/2003	375.50	08/07/2003	451.75	01/10/2003	417.00	25/12/2003	441.75
15/04/2003	391.50	09/07/2003	449.00	02/10/2003	434.00	26/12/2003	441.75
16/04/2003	417.00	10/07/2003	447.50	03/10/2003	437.00	29/12/2003	441.75
17/04/2003	384.25	11/07/2003	450.00	06/10/2003	445.00	30/12/2003	443.50
18/04/2003	398.50	14/07/2003	467.50	07/10/2003	436.00	31/12/2003	444.75
21/04/2003	398.50	15/07/2003	475.00	08/10/2003	433.00	01/01/2004	448.00
22/04/2003	401.50	16/07/2003	474.00	09/10/2003	431.00	02/01/2004	451.78
23/04/2003	407.75	17/07/2003	464.00	10/10/2003	429.75	05/01/2004	455.00
24/04/2003	418.75	18/07/2003	457.00	13/10/2003	425.00	06/01/2004	460.00
25/04/2003	417.00	21/07/2003	459.50	14/10/2003	430.00	07/01/2004	456.00
28/04/2003	404.00	22/07/2003	457.50	15/10/2003	425.50	08/01/2004	452.75
29/04/2003	427.25	23/07/2003	459.50	16/10/2003	422.00	09/01/2004	460.75
30/04/2003	421.50	24/07/2003	461.25	17/10/2003	425.00	12/01/2004	460.75
01/05/2003	409.00	25/07/2003	463.50	20/10/2003	420.50	13/01/2004	453.00
02/05/2003	407.00	28/07/2003	467.75	21/10/2003	424.00	14/01/2004	450.75
05/05/2003	416.00	29/07/2003	470.75	22/10/2003	421.00	15/01/2004	458.50
06/05/2003	420.00	30/07/2003	468.00	23/10/2003	409.00	16/01/2004	470.00
07/05/2003	422.75	31/07/2003	477.00	24/10/2003	415.00	19/01/2004	474.75
08/05/2003	426.00	01/08/2003	483.00	27/10/2003	417.00	20/01/2004	474.00
09/05/2003	415.50	04/08/2003	460.75	28/10/2003	418.75	21/01/2004	468.75
12/05/2003	420.75	05/08/2003	451.75	29/10/2003	417.50	22/01/2004	470.50
13/05/2003	421.50	06/08/2003	450.50	30/10/2003	408.00	23/01/2004	471.50
14/05/2003	410.98	07/08/2003	445.25	31/10/2003	411.00	26/01/2004	474.00
15/05/2003	421.00	08/08/2003	439.75	03/11/2003	410.00	27/01/2004	467.75
16/05/2003	436.75	11/08/2003	443.00	04/11/2003	409.25	28/01/2004	461.92
19/05/2003	430.50	12/08/2003	441.50	05/11/2003	409.75	29/01/2004	466.00
20/05/2003	419.75	13/08/2003	439.00	06/11/2003	407.50	30/01/2004	463.50
21/05/2003	420.75	14/08/2003	433.50	07/11/2003	409.00	02/02/2004	457.95
22/05/2003	414.00	15/08/2003	436.50	10/11/2003	411.50	03/02/2004	459.50
23/05/2003	426.75	18/08/2003	436.50	11/11/2003	406.50	04/02/2004	455.75
26/05/2003	419.75	19/08/2003	439.25	12/11/2003	407.25	05/02/2004	451.25
27/05/2003	420.50	20/08/2003	439.75	13/11/2003	413.50	06/02/2004	455.00
28/05/2003	430.00	21/08/2003	433.00	14/11/2003	408.25	09/02/2004	457.00
29/05/2003	435.00	22/08/2003	433.75	17/11/2003	404.00	10/02/2004	460.00
30/05/2003	459.25	25/08/2003	431.50	18/11/2003	401.75	11/02/2004	458.25
02/06/2003	456.00	26/08/2003	428.00	19/11/2003	394.75	12/02/2004	460.50
03/06/2003	467.50	27/08/2003	422.50	20/11/2003	399.75	13/02/2004	458.00
04/06/2003	466.25	28/08/2003	426.00	21/11/2003	397.50	16/02/2004	458.00
05/06/2003	460.00	29/08/2003	423.75	24/11/2003	400.00	17/02/2004	456.25
06/06/2003	456.00	01/09/2003	416.75	25/11/2003	412.25	18/02/2004	462.50
09/06/2003	457.00	02/09/2003	420.50	26/11/2003	418.95	19/02/2004	463.25
10/06/2003	453.75	03/09/2003	420.00	27/11/2003	416.25	20/02/2004	475.00
11/06/2003	449.75	04/09/2003	419.00	28/11/2003	413.25	23/02/2004	472.50
12/06/2003	452.25	05/09/2003	414.75	01/12/2003	414.25	24/02/2004	465.50
13/06/2003	452.75	08/09/2003	418.50	02/12/2003	414.50	25/02/2004	462.00
16/06/2003	448.75	09/09/2003	426.50	03/12/2003	411.75	26/02/2004	463.00
17/06/2003	466.00	10/09/2003	430.00	04/12/2003	413.00	27/02/2004	462.00

01/03/2004	450.25	25/05/2004	423.00	18/08/2004	405.25	11/11/2004	430.00
02/03/2004	447.00	26/05/2004	428.25	19/08/2004	408.00	12/11/2004	433.00
03/03/2004	442.00	27/05/2004	430.00	20/08/2004	403.00	15/11/2004	436.25
04/03/2004	445.75	28/05/2004	436.50	23/08/2004	406.50	16/11/2004	434.75
05/03/2004	456.25	31/05/2004	431.00	24/08/2004	409.50	17/11/2004	432.75
08/03/2004	458.00	01/06/2004	433.50	25/08/2004	411.00	18/11/2004	435.00
09/03/2004	438.00	02/06/2004	429.75	26/08/2004	412.50	19/11/2004	430.00
10/03/2004	447.75	03/06/2004	429.50	27/08/2004	418.00	22/11/2004	422.00
11/03/2004	437.50	04/06/2004	426.50	30/08/2004	418.25	23/11/2004	421.00
12/03/2004	428.00	07/06/2004	431.00	31/08/2004	418.00	24/11/2004	418.25
15/03/2004	432.25	08/06/2004	438.00	01/09/2004	420.75	25/11/2004	414.00
16/03/2004	432.00	09/06/2004	439.75	02/09/2004	424.50	26/11/2004	418.25
17/03/2004	415.00	10/06/2004	441.50	03/09/2004	427.50	29/11/2004	423.75
18/03/2004	418.00	11/06/2004	442.25	06/09/2004	432.00	30/11/2004	425.75
19/03/2004	417.00	14/06/2004	440.75	07/09/2004	433.00	01/12/2004	424.00
22/03/2004	408.25	15/06/2004	435.75	08/09/2004	428.50	02/12/2004	429.00
23/03/2004	407.00	16/06/2004	435.50	09/09/2004	428.00	03/12/2004	429.75
24/03/2004	412.25	17/06/2004	438.75	10/09/2004	429.75	06/12/2004	430.25
25/03/2004	409.75	18/06/2004	439.50	13/09/2004	431.00	07/12/2004	430.25
26/03/2004	415.25	21/06/2004	428.50	14/09/2004	431.50	08/12/2004	431.75
29/03/2004	412.50	22/06/2004	433.00	15/09/2004	432.00	09/12/2004	432.50
30/03/2004	416.50	23/06/2004	436.25	16/09/2004	428.00	10/12/2004	429.00
31/03/2004	414.00	24/06/2004	434.00	17/09/2004	427.50	13/12/2004	435.00
01/04/2004	416.00	25/06/2004	429.00	20/09/2004	432.00	14/12/2004	445.00
02/04/2004	418.50	28/06/2004	428.25	21/09/2004	430.00	15/12/2004	443.25
05/04/2004	422.00	29/06/2004	433.25	22/09/2004	433.50	16/12/2004	457.00
06/04/2004	427.50	30/06/2004	435.00	23/09/2004	433.00	17/12/2004	458.75
07/04/2004	423.75	01/07/2004	433.00	24/09/2004	425.75	20/12/2004	456.75
08/04/2004	417.00	02/07/2004	425.25	27/09/2004	427.00	21/12/2004	461.00
09/04/2004	418.25	05/07/2004	417.25	28/09/2004	424.75	22/12/2004	462.75
12/04/2004	418.25	06/07/2004	416.75	29/09/2004	430.00	23/12/2004	469.50
13/04/2004	420.00	07/07/2004	412.50	30/09/2004	435.75	24/12/2004	468.50
14/04/2004	415.00	08/07/2004	408.00	01/10/2004	434.00	27/12/2004	472.00
15/04/2004	414.00	09/07/2004	410.50	04/10/2004	443.75	28/12/2004	472.00
16/04/2004	414.00	12/07/2004	409.75	05/10/2004	444.25	29/12/2004	473.00
19/04/2004	417.00	13/07/2004	408.00	06/10/2004	447.25	30/12/2004	472.00
20/04/2004	423.50	14/07/2004	403.50	07/10/2004	450.00	31/12/2004	470.50
21/04/2004	425.00	15/07/2004	401.25	08/10/2004	445.50	03/01/2005	473.00
22/04/2004	428.25	16/07/2004	399.75	11/10/2004	448.00	04/01/2005	475.00
23/04/2004	431.50	19/07/2004	397.00	12/10/2004	450.00	05/01/2005	475.00
26/04/2004	428.50	20/07/2004	391.50	13/10/2004	445.00	06/01/2005	471.00
27/04/2004	430.00	21/07/2004	398.50	14/10/2004	439.50	07/01/2005	472.75
28/04/2004	427.00	22/07/2004	401.75	15/10/2004	436.25	10/01/2005	478.25
29/04/2004	427.00	23/07/2004	402.50	18/10/2004	433.00	11/01/2005	479.00
30/04/2004	424.50	26/07/2004	404.00	19/10/2004	425.00	12/01/2005	471.25
03/05/2004	421.50	27/07/2004	399.25	20/10/2004	435.00	13/01/2005	468.00
04/05/2004	425.00	28/07/2004	407.25	21/10/2004	433.50	14/01/2005	467.00
05/05/2004	418.00	29/07/2004	408.50	22/10/2004	430.25	17/01/2005	468.00
06/05/2004	421.00	30/07/2004	412.50	25/10/2004	423.75	18/01/2005	470.00
07/05/2004	421.00	02/08/2004	408.50	26/10/2004	424.50	19/01/2005	466.00
10/05/2004	410.00	03/08/2004	415.00	27/10/2004	426.50	20/01/2005	468.00
11/05/2004	415.00	04/08/2004	414.00	28/10/2004	430.00	21/01/2005	472.00
12/05/2004	421.50	05/08/2004	414.75	29/10/2004	435.00	24/01/2005	469.75
13/05/2004	417.75	06/08/2004	415.00	01/11/2004	432.00	25/01/2005	471.75
14/05/2004	421.25	09/08/2004	421.75	02/11/2004	438.25	26/01/2005	488.50
17/05/2004	421.25	10/08/2004	409.00	03/11/2004	440.00	27/01/2005	483.00
18/05/2004	422.75	11/08/2004	406.00	04/11/2004	437.00	28/01/2005	486.00
19/05/2004	418.00	12/08/2004	404.00	05/11/2004	435.25	31/01/2005	494.50
20/05/2004	422.00	13/08/2004	400.00	08/11/2004	433.75	01/02/2005	496.75
21/05/2004	426.50	16/08/2004	402.00	09/11/2004	434.25	02/02/2005	500.00
24/05/2004	424.00	17/08/2004	403.00	10/11/2004	433.75	03/02/2005	505.00

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07/02/2005	510.50
08/02/2005	506.25
09/02/2005	502.50
10/02/2005	496.50
11/02/2005	502.00
14/02/2005	510.00
15/02/2005	506.00
16/02/2005	508.00
17/02/2005	505.00
18/02/2005	507.25
21/02/2005	511.00
22/02/2005	507.00
23/02/2005	502.00
24/02/2005	496.25
25/02/2005	491.00
28/02/2005	494.00
01/03/2005	490.00
02/03/2005	495.75
03/03/2005	488.50
04/03/2005	500.00
07/03/2005	500.50
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14/03/2005	504.00
15/03/2005	500.00
16/03/2005	482.50
17/03/2005	476.00
18/03/2005	477.25
21/03/2005	479.00
22/03/2005	478.50
23/03/2005	474.50
24/03/2005	472.50
25/03/2005	475.50
28/03/2005	475.50
29/03/2005	475.00
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04/04/2005	478.00
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11/04/2005	482.50
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13/04/2005	477.00
14/04/2005	473.50
15/04/2005	472.00
18/04/2005	461.50
19/04/2005	462.00
20/04/2005	461.50
21/04/2005	456.00
22/04/2005	461.50
25/04/2005	459.00
26/04/2005	461.50
27/04/2005	455.00
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13/06/2005	464.50
14/06/2005	463.00
15/06/2005	469.00
16/06/2005	472.50
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21/06/2005	474.00
22/06/2005	475.00
23/06/2005	475.50
24/06/2005	475.00
27/06/2005	470.00
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07/07/2005	478.75
08/07/2005	478.00
11/07/2005	481.50
12/07/2005	486.00
13/07/2005	490.00
14/07/2005	495.00
15/07/2005	497.00
18/07/2005	494.25
19/07/2005	490.50
20/07/2005	487.50
21/07/2005	492.00
22/07/2005	489.50
25/07/2005	486.00
26/07/2005	484.25
27/07/2005	488.00
28/07/2005	490.75
29/07/2005	482.25
01/08/2005	484.00
02/08/2005	486.50
03/08/2005	486.00
04/08/2005	488.50
05/08/2005	486.75
08/08/2005	484.00
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11/08/2005	473.00
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15/08/2005	466.00
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19/08/2005	456.25
22/08/2005	457.00
23/08/2005	454.00
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26/08/2005	458.25
29/08/2005	457.50
30/08/2005	459.00
31/08/2005	458.00
01/09/2005	458.75
02/09/2005	459.50
05/09/2005	466.50
06/09/2005	484.00
07/09/2005	489.75
08/09/2005	489.75
09/09/2005	483.00
12/09/2005	483.50
13/09/2005	479.00
14/09/2005	473.50
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16/09/2005	467.25
19/09/2005	469.00
20/09/2005	470.00
21/09/2005	469.00
22/09/2005	462.50
23/09/2005	465.00
26/09/2005	466.00
27/09/2005	468.75
28/09/2005	470.00
29/09/2005	469.75
30/09/2005	472.00
03/10/2005	469.50
04/10/2005	468.50
05/10/2005	468.50
06/10/2005	462.50
07/10/2005	458.50
10/10/2005	456.50
11/10/2005	455.75
12/10/2005	453.50
13/10/2005	451.75
14/10/2005	450.50
17/10/2005	448.50
18/10/2005	449.00
19/10/2005	445.00
20/10/2005	447.50
21/10/2005	440.00
24/10/2005	443.25
25/10/2005	451.75
26/10/2005	453.00
27/10/2005	454.50
28/10/2005	450.75
31/10/2005	455.00
01/11/2005	459.50
02/11/2005	464.50
03/11/2005	465.25
04/11/2005	466.25
07/11/2005	468.50
08/11/2005	468.00
09/11/2005	471.00
10/11/2005	468.00
11/11/2005	468.50
14/11/2005	470.00
15/11/2005	472.00
16/11/2005	470.50
17/11/2005	470.50
18/11/2005	468.75
21/11/2005	477.25
22/11/2005	480.00
23/11/2005	478.50
24/11/2005	481.25
25/11/2005	482.25
28/11/2005	482.75
29/11/2005	476.00
30/11/2005	475.00
01/12/2005	471.25
02/12/2005	473.50
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06/12/2005	472.50
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13/12/2005	482.00
14/12/2005	482.25
15/12/2005	480.50
16/12/2005	478.00
19/12/2005	484.25
20/12/2005	486.75
21/12/2005	483.75
22/12/2005	488.75
23/12/2005	490.00
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29/12/2005	490.00
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03/01/2006	491.00
04/01/2006	492.75
05/01/2006	493.50
06/01/2006	493.50
09/01/2006	498.00
10/01/2006	498.75
11/01/2006	497.00

12/01/2006	514.00	07/04/2006	550.00	03/07/2006	534.00	26/09/2006	530.50
13/01/2006	511.00	10/04/2006	542.00	04/07/2006	536.00	27/09/2006	534.50
16/01/2006	510.25	11/04/2006	534.50	05/07/2006	537.50	28/09/2006	534.50
17/01/2006	509.50	12/04/2006	532.00	06/07/2006	539.00	29/09/2006	539.50
18/01/2006	503.00	13/04/2006	526.00	07/07/2006	541.50	02/10/2006	542.50
19/01/2006	507.75	14/04/2006	525.00	10/07/2006	546.00	03/10/2006	542.00
20/01/2006	518.00	17/04/2006	525.00	11/07/2006	539.50	04/10/2006	544.00
23/01/2006	508.00	18/04/2006	523.00	12/07/2006	543.00	05/10/2006	554.00
24/01/2006	515.00	19/04/2006	530.00	13/07/2006	533.00	06/10/2006	556.00
25/01/2006	507.00	20/04/2006	528.00	14/07/2006	522.00	09/10/2006	556.50
26/01/2006	510.00	21/04/2006	528.50	17/07/2006	518.00	10/10/2006	554.25
27/01/2006	516.00	24/04/2006	526.00	18/07/2006	515.00	11/10/2006	552.00
30/01/2006	517.50	25/04/2006	523.50	19/07/2006	518.00	12/10/2006	553.00
31/01/2006	510.00	26/04/2006	527.00	20/07/2006	532.50	13/10/2006	560.50
01/02/2006	514.50	27/04/2006	536.00	21/07/2006	529.50	16/10/2006	584.00
02/02/2006	535.00	28/04/2006	533.00	24/07/2006	526.50	17/10/2006	575.50
03/02/2006	525.50	01/05/2006	533.50	25/07/2006	538.00	18/10/2006	568.00
06/02/2006	533.00	02/05/2006	533.00	26/07/2006	540.00	19/10/2006	568.00
07/02/2006	524.25	03/05/2006	533.00	27/07/2006	541.00	20/10/2006	568.50
08/02/2006	521.75	04/05/2006	533.50	28/07/2006	539.00	23/10/2006	563.00
09/02/2006	536.75	05/05/2006	537.00	31/07/2006	544.00	24/10/2006	563.00
10/02/2006	547.50	08/05/2006	539.00	01/08/2006	536.00	25/10/2006	562.00
13/02/2006	550.00	09/05/2006	530.00	02/08/2006	538.00	26/10/2006	565.00
14/02/2006	554.00	10/05/2006	529.50	03/08/2006	529.00	27/10/2006	565.50
15/02/2006	550.00	11/05/2006	525.00	04/08/2006	520.00	30/10/2006	557.00
16/02/2006	550.00	12/05/2006	519.00	07/08/2006	525.00	31/10/2006	559.00
17/02/2006	547.00	15/05/2006	503.50	08/08/2006	523.00	01/11/2006	560.50
20/02/2006	547.00	16/05/2006	510.00	09/08/2006	513.50	02/11/2006	560.00
21/02/2006	547.00	17/05/2006	514.00	10/08/2006	506.50	03/11/2006	560.50
22/02/2006	545.50	18/05/2006	502.00	11/08/2006	510.50	06/11/2006	552.00
23/02/2006	546.00	19/05/2006	500.00	14/08/2006	511.00	07/11/2006	562.50
24/02/2006	556.50	22/05/2006	500.00	15/08/2006	514.50	08/11/2006	559.00
27/02/2006	570.00	23/05/2006	494.50	16/08/2006	518.00	09/11/2006	561.00
28/02/2006	567.00	24/05/2006	496.50	17/08/2006	519.50	10/11/2006	555.00
01/03/2006	554.00	25/05/2006	497.00	18/08/2006	521.00	13/11/2006	555.00
02/03/2006	554.50	26/05/2006	503.00	21/08/2006	523.50	14/11/2006	563.50
03/03/2006	550.00	29/05/2006	510.50	22/08/2006	523.00	15/11/2006	563.00
06/03/2006	548.25	30/05/2006	511.00	23/08/2006	524.50	16/11/2006	563.00
07/03/2006	546.25	31/05/2006	492.50	24/08/2006	522.50	17/11/2006	567.50
08/03/2006	522.00	01/06/2006	507.00	25/08/2006	529.00	20/11/2006	564.00
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10/03/2006	531.50	05/06/2006	518.50	29/08/2006	529.00	22/11/2006	569.00
13/03/2006	539.00	06/06/2006	510.00	30/08/2006	524.50	23/11/2006	564.50
14/03/2006	541.50	07/06/2006	511.50	31/08/2006	528.50	24/11/2006	559.50
15/03/2006	542.00	08/06/2006	512.50	01/09/2006	523.50	27/11/2006	553.00
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17/03/2006	550.00	12/06/2006	520.50	05/09/2006	534.50	29/11/2006	548.00
20/03/2006	556.00	13/06/2006	510.50	06/09/2006	535.00	30/11/2006	546.00
21/03/2006	561.00	14/06/2006	506.00	07/09/2006	528.00	01/12/2006	544.00
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23/03/2006	575.00	16/06/2006	532.00	11/09/2006	518.00	05/12/2006	543.00
24/03/2006	568.00	19/06/2006	525.00	12/09/2006	523.00	06/12/2006	539.50
27/03/2006	566.50	20/06/2006	520.00	13/09/2006	530.00	07/12/2006	544.00
28/03/2006	565.00	21/06/2006	525.50	14/09/2006	525.00	08/12/2006	550.00
29/03/2006	554.00	22/06/2006	527.00	15/09/2006	524.00	11/12/2006	559.00
30/03/2006	557.00	23/06/2006	524.50	18/09/2006	530.50	12/12/2006	557.50
31/03/2006	557.00	26/06/2006	524.00	19/09/2006	529.50	13/12/2006	555.50
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05/04/2006	547.00	29/06/2006	519.50	22/09/2006	529.50	18/12/2006	562.50
06/04/2006	546.00	30/06/2006	533.50	25/09/2006	529.00	19/12/2006	563.00

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21/12/2006	560.50	17/01/2007	583.00	13/02/2007	605.00	12/03/2007	554.00
22/12/2006	563.50	18/01/2007	584.00	14/02/2007	605.50	13/03/2007	549.50
25/12/2006	568.50	19/01/2007	576.50	15/02/2007	608.50	14/03/2007	534.50
26/12/2006	568.50	22/01/2007	581.50	16/02/2007	605.00	15/03/2007	540.00
27/12/2006	571.00	23/01/2007	583.00	19/02/2007	606.25	16/03/2007	533.00
28/12/2006	576.00	24/01/2007	582.00	20/02/2007	607.50	19/03/2007	545.00
29/12/2006	573.00	25/01/2007	590.00	21/02/2007	618.00	20/03/2007	551.00
01/01/2007	571.50	26/01/2007	583.50	22/02/2007	617.00	21/03/2007	554.50
02/01/2007	575.50	29/01/2007	582.00	23/02/2007	600.50	22/03/2007	567.50
03/01/2007	580.00	30/01/2007	588.00	26/02/2007	593.00	23/03/2007	568.50
04/01/2007	582.00	31/01/2007	584.50	27/02/2007	588.50	26/03/2007	574.00
05/01/2007	577.00	01/02/2007	586.00	28/02/2007	578.50	27/03/2007	567.00
08/01/2007	581.00	02/02/2007	586.00	01/03/2007	574.00	28/03/2007	563.00
09/01/2007	583.50	05/02/2007	590.50	02/03/2007	571.00	29/03/2007	557.50
10/01/2007	580.00	06/02/2007	593.00	05/03/2007	557.50	30/03/2007	559.50
11/01/2007	578.00	07/02/2007	597.00	06/03/2007	564.00		
12/01/2007	584.00	08/02/2007	595.00	07/03/2007	544.00		
15/01/2007	594.50	09/02/2007	603.00	08/03/2007	540.50		

Appendix C.3: *The historic open share prices of Royal Bank of Scotland (RBS) covers the period from 3rd July 2000 until 30th March 2007.*

Date	Prices						
		15/09/2000	1355.00	01/12/2000	1460.00	16/02/2001	1650.00
03/07/2000	1088.00	18/09/2000	1428.00	04/12/2000	1435.00	19/02/2001	1652.00
04/07/2000	1080.00	19/09/2000	1356.00	05/12/2000	1440.00	20/02/2001	1640.00
05/07/2000	1026.00	20/09/2000	1376.00	06/12/2000	1430.00	21/02/2001	1597.50
06/07/2000	1043.00	21/09/2000	1376.00	07/12/2000	1440.00	22/02/2001	1521.00
07/07/2000	1043.00	22/09/2000	1408.00	08/12/2000	1427.00	23/02/2001	1533.00
10/07/2000	1040.00	25/09/2000	1469.00	11/12/2000	1425.00	26/02/2001	1576.75
11/07/2000	1055.00	26/09/2000	1417.00	12/12/2000	1550.00	27/02/2001	1530.00
12/07/2000	1019.00	27/09/2000	1425.00	13/12/2000	1514.00	28/02/2001	1524.00
13/07/2000	1017.00	28/09/2000	1450.00	14/12/2000	1562.00	01/03/2001	1571.00
14/07/2000	1022.00	29/09/2000	1430.00	15/12/2000	1504.00	02/03/2001	1641.00
17/07/2000	1066.00	02/10/2000	1442.00	18/12/2000	1490.00	05/03/2001	1641.00
18/07/2000	1039.00	03/10/2000	1437.00	19/12/2000	1538.00	06/03/2001	1676.00
19/07/2000	1044.00	04/10/2000	1426.25	20/12/2000	1556.25	07/03/2001	1670.00
20/07/2000	1096.00	05/10/2000	1497.00	21/12/2000	1500.00	08/03/2001	1700.00
21/07/2000	1054.00	06/10/2000	1497.00	22/12/2000	1599.00	09/03/2001	1678.00
24/07/2000	1090.00	09/10/2000	1444.00	25/12/2000	1578.00	12/03/2001	1648.00
25/07/2000	1055.00	10/10/2000	1469.00	26/12/2000	1578.00	13/03/2001	1609.75
26/07/2000	1065.00	11/10/2000	1389.00	27/12/2000	1545.00	14/03/2001	1587.00
27/07/2000	1059.00	12/10/2000	1308.00	28/12/2000	1592.00	15/03/2001	1505.00
28/07/2000	1019.00	13/10/2000	1325.00	29/12/2000	1588.00	16/03/2001	1555.00
31/07/2000	1027.00	16/10/2000	1344.00	01/01/2001	1582.00	19/03/2001	1495.00
01/08/2000	1064.00	17/10/2000	1382.00	02/01/2001	1561.00	20/03/2001	1497.00
02/08/2000	900.00	18/10/2000	1399.00	03/01/2001	1554.00	21/03/2001	1500.00
03/08/2000	1245.00	19/10/2000	1387.00	04/01/2001	1580.00	22/03/2001	1425.00
04/08/2000	1205.00	20/10/2000	1389.00	05/01/2001	1570.00	23/03/2001	1370.00
07/08/2000	1220.00	23/10/2000	1430.00	08/01/2001	1652.00	26/03/2001	1335.00
08/08/2000	1250.00	24/10/2000	1461.00	09/01/2001	1653.00	27/03/2001	1444.00
09/08/2000	1100.00	25/10/2000	1474.00	10/01/2001	1632.00	28/03/2001	1520.00
10/08/2000	1286.00	26/10/2000	1490.00	11/01/2001	1612.00	29/03/2001	1496.00
11/08/2000	1254.00	27/10/2000	1480.00	12/01/2001	1590.00	30/03/2001	1548.00
14/08/2000	1283.00	30/10/2000	1497.00	15/01/2001	1605.75	02/04/2001	1596.00
15/08/2000	1295.00	31/10/2000	1506.00	16/01/2001	1602.00	03/04/2001	1593.00
16/08/2000	1315.00	01/11/2000	1558.00	17/01/2001	1625.00	04/04/2001	1553.00
17/08/2000	1337.00	02/11/2000	1550.50	18/01/2001	1705.00	05/04/2001	1554.00
18/08/2000	1307.00	03/11/2000	1588.00	19/01/2001	1654.00	06/04/2001	1600.00
21/08/2000	1334.00	06/11/2000	1573.25	22/01/2001	1576.00	09/04/2001	1575.00
22/08/2000	1326.00	07/11/2000	1566.00	23/01/2001	1631.00	10/04/2001	1575.00
23/08/2000	1368.00	08/11/2000	1536.00	24/01/2001	1652.00	11/04/2001	1533.00
24/08/2000	1377.00	09/11/2000	1509.00	25/01/2001	1644.00	12/04/2001	1605.00
25/08/2000	1308.00	10/11/2000	1499.00	26/01/2001	1613.00	13/04/2001	1615.00
28/08/2000	1291.00	13/11/2000	1477.00	29/01/2001	1600.00	16/04/2001	1615.00
29/08/2000	1282.00	14/11/2000	1475.00	30/01/2001	1639.00	17/04/2001	1615.00
30/08/2000	1282.00	15/11/2000	1513.00	31/01/2001	1640.00	18/04/2001	1600.00
31/08/2000	1244.00	16/11/2000	1540.00	01/02/2001	1625.00	19/04/2001	1589.00
01/09/2000	1257.00	17/11/2000	1530.00	02/02/2001	1636.00	20/04/2001	1668.00
04/09/2000	1250.00	20/11/2000	1496.25	05/02/2001	1585.00	23/04/2001	1660.00
05/09/2000	1280.00	21/11/2000	1482.50	06/02/2001	1603.00	24/04/2001	1611.00
06/09/2000	1329.00	22/11/2000	1477.00	07/02/2001	1610.00	25/04/2001	1638.00
07/09/2000	1312.50	23/11/2000	1420.00	08/02/2001	1576.00	26/04/2001	1641.00
08/09/2000	1313.00	24/11/2000	1425.00	09/02/2001	1615.00	27/04/2001	1635.00
11/09/2000	1330.00	27/11/2000	1433.00	12/02/2001	1595.00	30/04/2001	1645.00
12/09/2000	1340.00	28/11/2000	1475.00	13/02/2001	1612.00	01/05/2001	1610.00
13/09/2000	1351.50	29/11/2000	1421.00	14/02/2001	1646.25	02/05/2001	1597.00
14/09/2000	1350.00	30/11/2000	1397.50	15/02/2001	1649.00	03/05/2001	1582.00

04/05/2001	1588.00	30/07/2001	1565.00	23/10/2001	1633.00	16/01/2002	1723.00
07/05/2001	1571.00	31/07/2001	1557.00	24/10/2001	1670.00	17/01/2002	1699.00
08/05/2001	1588.00	01/08/2001	1585.00	25/10/2001	1668.00	18/01/2002	1705.00
09/05/2001	1594.00	02/08/2001	1647.00	26/10/2001	1667.00	21/01/2002	1712.00
10/05/2001	1647.00	03/08/2001	1664.00	29/10/2001	1686.00	22/01/2002	1706.00
11/05/2001	1669.00	06/08/2001	1692.00	30/10/2001	1625.00	23/01/2002	1725.00
14/05/2001	1678.00	07/08/2001	1620.00	31/10/2001	1610.00	24/01/2002	1757.00
15/05/2001	1657.00	08/08/2001	1651.00	01/11/2001	1670.00	25/01/2002	1788.00
16/05/2001	1628.00	09/08/2001	1691.00	02/11/2001	1644.00	28/01/2002	1796.00
17/05/2001	1653.00	10/08/2001	1715.00	05/11/2001	1669.00	29/01/2002	1846.00
18/05/2001	1654.00	13/08/2001	1700.00	06/11/2001	1718.00	30/01/2002	1777.00
21/05/2001	1646.00	14/08/2001	1731.00	07/11/2001	1740.00	31/01/2002	1776.00
22/05/2001	1670.00	15/08/2001	1745.00	08/11/2001	1707.00	01/02/2002	1810.00
23/05/2001	1661.00	16/08/2001	1741.00	09/11/2001	1674.00	04/02/2002	1810.00
24/05/2001	1632.00	17/08/2001	1773.00	12/11/2001	1687.00	05/02/2002	1793.00
25/05/2001	1673.00	20/08/2001	1770.00	13/11/2001	1624.00	06/02/2002	1795.00
28/05/2001	1643.00	21/08/2001	1757.00	14/11/2001	1680.00	07/02/2002	1745.00
29/05/2001	1643.00	22/08/2001	1763.00	15/11/2001	1644.00	08/02/2002	1773.00
30/05/2001	1634.00	23/08/2001	1775.00	16/11/2001	1673.00	11/02/2002	1746.00
31/05/2001	1612.00	24/08/2001	1761.92	19/11/2001	1711.00	12/02/2002	1780.00
01/06/2001	1614.00	27/08/2001	1772.00	20/11/2001	1700.00	13/02/2002	1759.00
04/06/2001	1670.00	28/08/2001	1773.00	21/11/2001	1678.00	14/02/2002	1753.00
05/06/2001	1658.00	29/08/2001	1771.00	22/11/2001	1700.00	15/02/2002	1795.00
06/06/2001	1694.75	30/08/2001	1763.00	23/11/2001	1686.00	18/02/2002	1770.00
07/06/2001	1750.00	31/08/2001	1707.22	26/11/2001	1678.00	19/02/2002	1768.00
08/06/2001	1749.00	03/09/2001	1737.00	27/11/2001	1688.00	20/02/2002	1719.00
11/06/2001	1717.00	04/09/2001	1698.00	28/11/2001	1657.00	21/02/2002	1704.00
12/06/2001	1708.00	05/09/2001	1717.00	29/11/2001	1608.00	22/02/2002	1680.00
13/06/2001	1687.00	06/09/2001	1720.00	30/11/2001	1620.00	25/02/2002	1693.00
14/06/2001	1720.00	07/09/2001	1672.00	03/12/2001	1620.00	26/02/2002	1758.00
15/06/2001	1730.00	10/09/2001	1615.50	04/12/2001	1599.00	27/02/2002	1748.00
18/06/2001	1750.00	11/09/2001	1576.00	05/12/2001	1584.00	28/02/2002	1723.00
19/06/2001	1685.00	12/09/2001	1402.00	06/12/2001	1589.00	01/03/2002	1770.00
20/06/2001	1672.67	13/09/2001	1492.00	07/12/2001	1657.00	04/03/2002	1815.00
21/06/2001	1667.50	14/09/2001	1559.00	10/12/2001	1606.00	05/03/2002	1870.00
22/06/2001	1650.00	17/09/2001	1533.00	11/12/2001	1570.00	06/03/2002	1844.00
25/06/2001	1649.00	18/09/2001	1565.00	12/12/2001	1555.00	07/03/2002	1855.00
26/06/2001	1690.00	19/09/2001	1494.00	13/12/2001	1566.00	08/03/2002	1834.00
27/06/2001	1633.00	20/09/2001	1409.50	14/12/2001	1527.00	11/03/2002	1875.00
28/06/2001	1668.00	21/09/2001	1238.00	17/12/2001	1560.00	12/03/2002	1869.00
29/06/2001	1655.00	24/09/2001	1285.00	18/12/2001	1659.00	13/03/2002	1819.00
02/07/2001	1565.00	25/09/2001	1358.00	19/12/2001	1616.00	14/03/2002	1860.00
03/07/2001	1608.00	26/09/2001	1417.00	20/12/2001	1650.00	15/03/2002	1819.00
04/07/2001	1628.00	27/09/2001	1390.00	21/12/2001	1601.00	18/03/2002	1845.00
05/07/2001	1600.00	28/09/2001	1496.00	24/12/2001	1629.00	19/03/2002	1845.00
06/07/2001	1583.00	01/10/2001	1500.00	25/12/2001	1665.00	20/03/2002	1858.00
09/07/2001	1489.40	02/10/2001	1490.00	26/12/2001	1665.00	21/03/2002	1823.00
10/07/2001	1550.00	03/10/2001	1530.00	27/12/2001	1668.00	22/03/2002	1823.00
11/07/2001	1548.00	04/10/2001	1502.00	28/12/2001	1689.00	25/03/2002	1816.00
12/07/2001	1544.00	05/10/2001	1549.00	31/12/2001	1675.00	26/03/2002	1797.00
13/07/2001	1540.00	08/10/2001	1553.00	01/01/2002	1672.00	27/03/2002	1800.00
16/07/2001	1533.00	09/10/2001	1545.00	02/01/2002	1670.00	28/03/2002	1780.00
17/07/2001	1495.00	10/10/2001	1550.00	03/01/2002	1685.00	29/03/2002	1780.00
18/07/2001	1482.00	11/10/2001	1634.00	04/01/2002	1706.00	01/04/2002	1780.00
19/07/2001	1514.00	12/10/2001	1648.70	07/01/2002	1710.00	02/04/2002	1791.00
20/07/2001	1540.00	15/10/2001	1600.00	08/01/2002	1691.00	03/04/2002	1800.00
23/07/2001	1528.00	16/10/2001	1594.00	09/01/2002	1688.00	04/04/2002	1778.00
24/07/2001	1551.00	17/10/2001	1610.00	10/01/2002	1709.00	05/04/2002	1798.00
25/07/2001	1565.00	18/10/2001	1637.00	11/01/2002	1723.00	08/04/2002	1816.00
26/07/2001	1528.00	19/10/2001	1657.00	14/01/2002	1720.00	09/04/2002	1802.00
27/07/2001	1515.00	22/10/2001	1595.00	15/01/2002	1679.00	10/04/2002	1803.00

11/04/2002	1839.00	05/07/2002	1745.00	30/09/2002	1180.00	24/12/2002	1499.00
12/04/2002	1827.00	08/07/2002	1790.00	01/10/2002	1194.00	25/12/2002	1508.00
15/04/2002	1867.00	09/07/2002	1752.00	02/10/2002	1273.00	26/12/2002	1508.00
16/04/2002	1880.00	10/07/2002	1728.00	03/10/2002	1293.00	27/12/2002	1508.00
17/04/2002	1911.00	11/07/2002	1674.00	04/10/2002	1282.00	30/12/2002	1440.00
18/04/2002	1914.00	12/07/2002	1638.00	07/10/2002	1239.00	31/12/2002	1471.00
19/04/2002	1939.00	15/07/2002	1555.00	08/10/2002	1281.00	01/01/2003	1488.00
22/04/2002	1940.00	16/07/2002	1483.00	09/10/2002	1252.00	02/01/2003	1493.00
23/04/2002	1942.00	17/07/2002	1470.00	10/10/2002	1250.00	03/01/2003	1528.00
24/04/2002	1933.00	18/07/2002	1600.00	11/10/2002	1322.00	06/01/2003	1539.00
25/04/2002	1981.00	19/07/2002	1619.00	14/10/2002	1420.00	07/01/2003	1477.00
26/04/2002	2025.00	22/07/2002	1536.00	15/10/2002	1375.00	08/01/2003	1480.00
29/04/2002	1984.00	23/07/2002	1520.00	16/10/2002	1500.00	09/01/2003	1463.00
30/04/2002	1970.00	24/07/2002	1468.00	17/10/2002	1490.00	10/01/2003	1480.00
01/05/2002	1965.00	25/07/2002	1495.00	18/10/2002	1550.00	13/01/2003	1509.00
02/05/2002	1953.00	26/07/2002	1535.00	21/10/2002	1535.00	14/01/2003	1494.00
03/05/2002	1975.00	29/07/2002	1596.00	22/10/2002	1580.00	15/01/2003	1489.00
06/05/2002	2060.00	30/07/2002	1695.00	23/10/2002	1563.00	16/01/2003	1455.00
07/05/2002	2050.00	31/07/2002	1640.00	24/10/2002	1491.00	17/01/2003	1442.00
08/05/2002	1998.00	01/08/2002	1699.00	25/10/2002	1515.00	20/01/2003	1414.00
09/05/2002	2015.00	02/08/2002	1520.00	28/10/2002	1536.00	21/01/2003	1385.00
10/05/2002	1995.00	05/08/2002	1468.00	29/10/2002	1525.00	22/01/2003	1350.00
13/05/2002	2016.00	06/08/2002	1428.00	30/10/2002	1482.00	23/01/2003	1354.00
14/05/2002	2045.00	07/08/2002	1577.00	31/10/2002	1465.00	24/01/2003	1321.00
15/05/2002	2055.00	08/08/2002	1460.00	01/11/2002	1502.00	27/01/2003	1316.00
16/05/2002	2032.00	09/08/2002	1560.00	04/11/2002	1503.00	28/01/2003	1314.00
17/05/2002	2020.00	12/08/2002	1552.00	05/11/2002	1525.00	29/01/2003	1293.00
20/05/2002	2030.00	13/08/2002	1553.00	06/11/2002	1571.00	30/01/2003	1305.00
21/05/2002	1988.00	14/08/2002	1511.00	07/11/2002	1543.00	31/01/2003	1316.00
22/05/2002	1960.00	15/08/2002	1555.00	08/11/2002	1521.00	03/02/2003	1388.00
23/05/2002	1969.00	16/08/2002	1568.00	11/11/2002	1510.00	04/02/2003	1384.00
24/05/2002	2008.00	19/08/2002	1605.00	12/11/2002	1508.00	05/02/2003	1394.00
27/05/2002	2011.00	20/08/2002	1599.00	13/11/2002	1505.00	06/02/2003	1423.00
28/05/2002	1998.00	21/08/2002	1630.00	14/11/2002	1489.00	07/02/2003	1376.00
29/05/2002	1973.00	22/08/2002	1648.00	15/11/2002	1525.00	10/02/2003	1400.00
30/05/2002	1995.00	23/08/2002	1622.00	18/11/2002	1518.00	11/02/2003	1409.00
31/05/2002	1957.00	26/08/2002	1618.00	19/11/2002	1507.00	12/02/2003	1430.00
03/06/2002	1990.00	27/08/2002	1623.00	20/11/2002	1510.00	13/02/2003	1449.00
04/06/2002	1990.00	28/08/2002	1583.00	21/11/2002	1517.00	14/02/2003	1484.00
05/06/2002	1962.00	29/08/2002	1570.00	22/11/2002	1551.00	17/02/2003	1470.00
06/06/2002	1975.00	30/08/2002	1543.00	25/11/2002	1592.00	18/02/2003	1476.00
07/06/2002	1987.00	02/09/2002	1517.00	26/11/2002	1595.00	19/02/2003	1457.00
10/06/2002	1950.00	03/09/2002	1503.00	27/11/2002	1600.00	20/02/2003	1435.00
11/06/2002	1946.00	04/09/2002	1495.00	28/11/2002	1603.00	21/02/2003	1442.00
12/06/2002	1937.00	05/09/2002	1490.00	29/11/2002	1615.00	24/02/2003	1415.00
13/06/2002	1957.00	06/09/2002	1533.00	02/12/2002	1648.00	25/02/2003	1407.00
14/06/2002	1844.00	09/09/2002	1530.00	03/12/2002	1614.00	26/02/2003	1420.00
17/06/2002	1850.00	10/09/2002	1513.00	04/12/2002	1540.00	27/02/2003	1377.00
18/06/2002	1838.00	11/09/2002	1552.00	05/12/2002	1538.00	28/02/2003	1408.00
19/06/2002	1782.00	12/09/2002	1535.00	06/12/2002	1520.00	03/03/2003	1460.00
20/06/2002	1739.00	13/09/2002	1495.00	09/12/2002	1533.00	04/03/2003	1455.00
21/06/2002	1735.00	16/09/2002	1476.00	10/12/2002	1478.00	05/03/2003	1389.00
24/06/2002	1810.00	17/09/2002	1508.00	11/12/2002	1490.00	06/03/2003	1376.00
25/06/2002	1834.00	18/09/2002	1427.00	12/12/2002	1518.00	07/03/2003	1380.25
26/06/2002	1815.00	19/09/2002	1385.00	13/12/2002	1497.00	10/03/2003	1361.00
27/06/2002	1840.00	20/09/2002	1303.00	16/12/2002	1419.00	11/03/2003	1313.00
28/06/2002	1823.00	23/09/2002	1305.00	17/12/2002	1520.00	12/03/2003	1336.00
01/07/2002	1843.00	24/09/2002	1228.00	18/12/2002	1461.00	13/03/2003	1260.00
02/07/2002	1810.00	25/09/2002	1196.00	19/12/2002	1446.00	14/03/2003	1366.00
03/07/2002	1775.00	26/09/2002	1240.00	20/12/2002	1412.00	17/03/2003	1350.00
04/07/2002	1705.00	27/09/2002	1260.00	23/12/2002	1447.00	18/03/2003	1435.00

19/03/2003	1416.00	12/06/2003	1730.00	05/09/2003	1538.00	01/12/2003	1636.00
20/03/2003	1458.00	13/06/2003	1740.00	08/09/2003	1576.00	02/12/2003	1630.67
21/03/2003	1480.00	16/06/2003	1727.00	09/09/2003	1601.00	03/12/2003	1618.00
24/03/2003	1509.00	17/06/2003	1767.00	10/09/2003	1589.00	04/12/2003	1639.00
25/03/2003	1447.00	18/06/2003	1750.00	11/09/2003	1570.00	05/12/2003	1637.22
26/03/2003	1450.00	19/06/2003	1780.00	12/09/2003	1580.00	08/12/2003	1627.00
27/03/2003	1468.00	20/06/2003	1743.00	15/09/2003	1582.00	09/12/2003	1630.00
28/03/2003	1462.00	23/06/2003	1740.66	16/09/2003	1594.00	10/12/2003	1596.50
31/03/2003	1449.00	24/06/2003	1704.00	17/09/2003	1627.00	11/12/2003	1584.28
01/04/2003	1427.00	25/06/2003	1709.00	18/09/2003	1624.00	12/12/2003	1602.00
02/04/2003	1465.00	26/06/2003	1698.00	19/09/2003	1635.00	15/12/2003	1618.00
03/04/2003	1498.00	27/06/2003	1715.00	22/09/2003	1619.00	16/12/2003	1601.00
04/04/2003	1525.00	30/06/2003	1698.00	23/09/2003	1625.00	17/12/2003	1604.26
07/04/2003	1605.00	01/07/2003	1664.00	24/09/2003	1638.00	18/12/2003	1616.00
08/04/2003	1584.00	02/07/2003	1700.00	25/09/2003	1608.00	19/12/2003	1629.60
09/04/2003	1600.00	03/07/2003	1734.00	26/09/2003	1597.00	22/12/2003	1618.00
10/04/2003	1600.00	04/07/2003	1693.00	29/09/2003	1592.00	23/12/2003	1639.00
11/04/2003	1606.00	07/07/2003	1699.00	30/09/2003	1573.00	24/12/2003	1639.00
14/04/2003	1561.00	08/07/2003	1695.00	01/10/2003	1540.00	25/12/2003	1648.00
15/04/2003	1579.00	09/07/2003	1680.00	02/10/2003	1603.00	26/12/2003	1648.00
16/04/2003	1643.00	10/07/2003	1690.00	03/10/2003	1626.00	29/12/2003	1630.00
17/04/2003	1589.00	11/07/2003	1672.00	06/10/2003	1630.00	30/12/2003	1645.00
18/04/2003	1611.00	14/07/2003	1707.00	07/10/2003	1623.00	31/12/2003	1645.00
21/04/2003	1611.00	15/07/2003	1720.00	08/10/2003	1622.00	01/01/2004	1646.00
22/04/2003	1610.00	16/07/2003	1737.00	09/10/2003	1626.00	02/01/2004	1655.00
23/04/2003	1646.00	17/07/2003	1742.00	10/10/2003	1633.00	05/01/2004	1648.15
24/04/2003	1625.00	18/07/2003	1738.00	13/10/2003	1630.00	06/01/2004	1650.00
25/04/2003	1616.00	21/07/2003	1727.00	14/10/2003	1654.00	07/01/2004	1672.00
28/04/2003	1605.00	22/07/2003	1707.00	15/10/2003	1647.00	08/01/2004	1652.00
29/04/2003	1667.00	23/07/2003	1748.00	16/10/2003	1641.00	09/01/2004	1652.00
30/04/2003	1648.00	24/07/2003	1754.00	17/10/2003	1656.00	12/01/2004	1670.00
01/05/2003	1641.00	25/07/2003	1770.00	20/10/2003	1624.00	13/01/2004	1675.00
02/05/2003	1634.00	28/07/2003	1780.00	21/10/2003	1644.00	14/01/2004	1667.00
05/05/2003	1625.00	29/07/2003	1770.00	22/10/2003	1631.00	15/01/2004	1710.00
06/05/2003	1636.00	30/07/2003	1763.00	23/10/2003	1550.00	16/01/2004	1716.00
07/05/2003	1636.00	31/07/2003	1740.00	24/10/2003	1587.00	19/01/2004	1720.00
08/05/2003	1625.00	01/08/2003	1761.00	27/10/2003	1577.00	20/01/2004	1683.00
09/05/2003	1615.00	04/08/2003	1730.00	28/10/2003	1580.00	21/01/2004	1664.40
12/05/2003	1641.00	05/08/2003	1720.00	29/10/2003	1569.00	22/01/2004	1682.23
13/05/2003	1634.00	06/08/2003	1660.00	30/10/2003	1555.00	23/01/2004	1674.00
14/05/2003	1613.00	07/08/2003	1652.00	31/10/2003	1583.00	26/01/2004	1670.00
15/05/2003	1601.00	08/08/2003	1629.00	03/11/2003	1566.00	27/01/2004	1655.00
16/05/2003	1627.00	11/08/2003	1644.00	04/11/2003	1550.00	28/01/2004	1637.00
19/05/2003	1610.00	12/08/2003	1652.00	05/11/2003	1584.00	29/01/2004	1647.85
20/05/2003	1590.00	13/08/2003	1660.00	06/11/2003	1567.00	30/01/2004	1629.90
21/05/2003	1573.00	14/08/2003	1621.00	07/11/2003	1545.00	02/02/2004	1613.99
22/05/2003	1583.00	15/08/2003	1618.00	10/11/2003	1542.00	03/02/2004	1600.00
23/05/2003	1575.00	18/08/2003	1654.00	11/11/2003	1556.00	04/02/2004	1620.00
26/05/2003	1550.00	19/08/2003	1638.00	12/11/2003	1558.00	05/02/2004	1634.00
27/05/2003	1554.00	20/08/2003	1618.00	13/11/2003	1605.00	06/02/2004	1625.00
28/05/2003	1570.00	21/08/2003	1582.00	14/11/2003	1591.00	09/02/2004	1645.00
29/05/2003	1599.00	22/08/2003	1607.00	17/11/2003	1581.00	10/02/2004	1639.00
30/05/2003	1605.00	25/08/2003	1612.00	18/11/2003	1580.00	11/02/2004	1638.00
02/06/2003	1619.40	26/08/2003	1606.00	19/11/2003	1571.00	12/02/2004	1630.00
03/06/2003	1595.00	27/08/2003	1600.00	20/11/2003	1589.00	13/02/2004	1619.47
04/06/2003	1620.00	28/08/2003	1594.00	21/11/2003	1569.00	16/02/2004	1627.00
05/06/2003	1625.00	29/08/2003	1593.00	24/11/2003	1558.00	17/02/2004	1644.00
06/06/2003	1635.00	01/09/2003	1585.00	25/11/2003	1594.00	18/02/2004	1658.00
09/06/2003	1609.00	02/09/2003	1567.00	26/11/2003	1611.00	19/02/2004	1669.00
10/06/2003	1619.00	03/09/2003	1583.00	27/11/2003	1625.00	20/02/2004	1728.00
11/06/2003	1656.00	04/09/2003	1569.00	28/11/2003	1629.00	23/02/2004	1717.00

24/02/2004	1713.00	19/05/2004	1655.00	12/08/2004	1467.00	05/11/2004	1664.00
25/02/2004	1709.00	20/05/2004	1684.00	13/08/2004	1468.00	08/11/2004	1653.00
26/02/2004	1720.00	21/05/2004	1680.00	16/08/2004	1464.00	09/11/2004	1625.00
27/02/2004	1734.00	24/05/2004	1677.00	17/08/2004	1492.00	10/11/2004	1622.00
01/03/2004	1716.00	25/05/2004	1669.00	18/08/2004	1488.00	11/11/2004	1631.00
02/03/2004	1748.00	26/05/2004	1685.00	19/08/2004	1512.00	12/11/2004	1646.00
03/03/2004	1716.00	27/05/2004	1656.00	20/08/2004	1515.00	15/11/2004	1643.00
04/03/2004	1745.00	28/05/2004	1669.00	23/08/2004	1539.00	16/11/2004	1637.00
05/03/2004	1761.00	31/05/2004	1647.00	24/08/2004	1528.00	17/11/2004	1631.00
08/03/2004	1754.00	01/06/2004	1657.00	25/08/2004	1542.00	18/11/2004	1633.00
09/03/2004	1756.00	02/06/2004	1645.00	26/08/2004	1545.00	19/11/2004	1643.00
10/03/2004	1726.00	03/06/2004	1658.00	27/08/2004	1567.00	22/11/2004	1634.00
11/03/2004	1719.00	04/06/2004	1652.00	30/08/2004	1572.00	23/11/2004	1648.00
12/03/2004	1674.00	07/06/2004	1660.00	31/08/2004	1566.00	24/11/2004	1626.00
15/03/2004	1697.00	08/06/2004	1675.00	01/09/2004	1557.00	25/11/2004	1614.00
16/03/2004	1657.00	09/06/2004	1663.00	02/09/2004	1568.00	26/11/2004	1624.00
17/03/2004	1678.00	10/06/2004	1674.00	03/09/2004	1583.00	29/11/2004	1620.00
18/03/2004	1704.00	11/06/2004	1667.00	06/09/2004	1591.00	30/11/2004	1626.00
19/03/2004	1690.00	14/06/2004	1667.00	07/09/2004	1590.00	01/12/2004	1613.00
22/03/2004	1665.00	15/06/2004	1646.00	08/09/2004	1588.00	02/12/2004	1657.00
23/03/2004	1667.00	16/06/2004	1647.00	09/09/2004	1555.00	03/12/2004	1672.00
24/03/2004	1657.00	17/06/2004	1657.00	10/09/2004	1567.00	06/12/2004	1670.00
25/03/2004	1646.00	18/06/2004	1661.00	13/09/2004	1568.00	07/12/2004	1675.00
26/03/2004	1671.00	21/06/2004	1670.00	14/09/2004	1561.00	08/12/2004	1647.00
29/03/2004	1671.00	22/06/2004	1650.00	15/09/2004	1563.00	09/12/2004	1660.00
30/03/2004	1683.00	23/06/2004	1640.00	16/09/2004	1565.00	10/12/2004	1682.00
31/03/2004	1677.00	24/06/2004	1640.00	17/09/2004	1557.00	13/12/2004	1673.00
01/04/2004	1665.00	25/06/2004	1610.00	20/09/2004	1556.00	14/12/2004	1734.00
02/04/2004	1687.00	28/06/2004	1612.00	21/09/2004	1569.00	15/12/2004	1705.00
05/04/2004	1698.00	29/06/2004	1627.00	22/09/2004	1584.00	16/12/2004	1713.00
06/04/2004	1683.00	30/06/2004	1613.00	23/09/2004	1585.00	17/12/2004	1719.00
07/04/2004	1682.00	01/07/2004	1597.00	24/09/2004	1596.00	20/12/2004	1717.00
08/04/2004	1690.00	02/07/2004	1576.00	27/09/2004	1613.00	21/12/2004	1725.00
09/04/2004	1687.00	05/07/2004	1570.00	28/09/2004	1589.00	22/12/2004	1719.00
12/04/2004	1687.00	06/07/2004	1580.00	29/09/2004	1608.00	23/12/2004	1738.00
13/04/2004	1701.00	07/07/2004	1555.00	30/09/2004	1610.00	24/12/2004	1732.00
14/04/2004	1692.00	08/07/2004	1536.00	01/10/2004	1600.00	27/12/2004	1740.00
15/04/2004	1685.00	09/07/2004	1558.00	04/10/2004	1630.00	28/12/2004	1740.00
16/04/2004	1680.00	12/07/2004	1569.00	05/10/2004	1639.00	29/12/2004	1725.00
19/04/2004	1679.00	13/07/2004	1563.00	06/10/2004	1658.00	30/12/2004	1750.00
20/04/2004	1700.00	14/07/2004	1560.00	07/10/2004	1671.00	31/12/2004	1750.00
21/04/2004	1710.00	15/07/2004	1558.00	08/10/2004	1665.00	03/01/2005	1752.00
22/04/2004	1717.00	16/07/2004	1528.00	11/10/2004	1680.00	04/01/2005	1748.00
23/04/2004	1729.00	19/07/2004	1526.00	12/10/2004	1665.00	05/01/2005	1760.00
26/04/2004	1724.00	20/07/2004	1518.00	13/10/2004	1635.00	06/01/2005	1759.00
27/04/2004	1730.00	21/07/2004	1547.00	14/10/2004	1618.00	07/01/2005	1746.00
28/04/2004	1722.00	22/07/2004	1537.00	15/10/2004	1615.00	10/01/2005	1777.00
29/04/2004	1718.00	23/07/2004	1519.00	18/10/2004	1606.00	11/01/2005	1774.00
30/04/2004	1705.00	26/07/2004	1504.00	19/10/2004	1620.00	12/01/2005	1772.00
03/05/2004	1693.00	27/07/2004	1511.00	20/10/2004	1615.00	13/01/2005	1753.00
04/05/2004	1700.00	28/07/2004	1529.00	21/10/2004	1614.00	14/01/2005	1734.00
05/05/2004	1660.00	29/07/2004	1551.00	22/10/2004	1595.00	17/01/2005	1738.00
06/05/2004	1641.00	30/07/2004	1561.00	25/10/2004	1590.00	18/01/2005	1751.00
07/05/2004	1652.00	02/08/2004	1540.00	26/10/2004	1585.00	19/01/2005	1746.00
10/05/2004	1635.00	03/08/2004	1552.00	27/10/2004	1591.00	20/01/2005	1729.00
11/05/2004	1651.00	04/08/2004	1505.00	28/10/2004	1605.00	21/01/2005	1748.00
12/05/2004	1675.00	05/08/2004	1533.00	29/10/2004	1617.00	24/01/2005	1736.00
13/05/2004	1679.00	06/08/2004	1517.00	01/11/2004	1614.00	25/01/2005	1755.00
14/05/2004	1675.00	09/08/2004	1502.00	02/11/2004	1645.00	26/01/2005	1763.00
17/05/2004	1657.00	10/08/2004	1515.00	03/11/2004	1660.00	27/01/2005	1734.00
18/05/2004	1660.00	11/08/2004	1495.00	04/11/2004	1650.00	28/01/2005	1765.00

31/01/2005	1770.00	26/04/2005	1620.00	20/07/2005	1727.00	13/10/2005	1596.00
01/02/2005	1767.00	27/04/2005	1590.00	21/07/2005	1728.00	14/10/2005	1584.00
02/02/2005	1773.00	28/04/2005	1590.00	22/07/2005	1714.00	17/10/2005	1592.00
03/02/2005	1770.00	29/04/2005	1581.00	25/07/2005	1730.00	18/10/2005	1570.00
04/02/2005	1763.00	02/05/2005	1574.00	26/07/2005	1715.00	19/10/2005	1552.00
07/02/2005	1768.00	03/05/2005	1586.00	27/07/2005	1708.00	20/10/2005	1545.00
08/02/2005	1768.00	04/05/2005	1604.00	28/07/2005	1708.00	21/10/2005	1527.00
09/02/2005	1761.00	05/05/2005	1613.00	29/07/2005	1712.00	24/10/2005	1552.00
10/02/2005	1757.00	06/05/2005	1626.00	01/08/2005	1696.00	25/10/2005	1565.00
11/02/2005	1805.00	09/05/2005	1642.00	02/08/2005	1704.00	26/10/2005	1570.00
14/02/2005	1826.00	10/05/2005	1639.00	03/08/2005	1717.00	27/10/2005	1563.00
15/02/2005	1826.00	11/05/2005	1624.00	04/08/2005	1665.00	28/10/2005	1550.00
16/02/2005	1823.00	12/05/2005	1633.00	05/08/2005	1628.00	31/10/2005	1549.00
17/02/2005	1807.00	13/05/2005	1639.00	08/08/2005	1648.00	01/11/2005	1561.00
18/02/2005	1814.00	16/05/2005	1640.00	09/08/2005	1626.00	02/11/2005	1576.00
21/02/2005	1839.00	17/05/2005	1640.00	10/08/2005	1608.00	03/11/2005	1612.00
22/02/2005	1820.00	18/05/2005	1640.00	11/08/2005	1597.00	04/11/2005	1634.00
23/02/2005	1795.00	19/05/2005	1650.00	12/08/2005	1604.00	07/11/2005	1633.00
24/02/2005	1821.00	20/05/2005	1639.00	15/08/2005	1607.00	08/11/2005	1647.00
25/02/2005	1789.00	23/05/2005	1638.00	16/08/2005	1617.00	09/11/2005	1642.00
28/02/2005	1780.00	24/05/2005	1653.00	17/08/2005	1610.00	10/11/2005	1636.00
01/03/2005	1789.00	25/05/2005	1660.00	18/08/2005	1636.00	11/11/2005	1650.00
02/03/2005	1809.00	26/05/2005	1632.00	19/08/2005	1643.00	14/11/2005	1667.00
03/03/2005	1799.00	27/05/2005	1607.00	22/08/2005	1643.00	15/11/2005	1661.00
04/03/2005	1805.00	30/05/2005	1615.00	23/08/2005	1647.00	16/11/2005	1674.00
07/03/2005	1806.00	31/05/2005	1622.00	24/08/2005	1648.00	17/11/2005	1673.00
08/03/2005	1796.00	01/06/2005	1616.00	25/08/2005	1636.00	18/11/2005	1676.00
09/03/2005	1747.00	02/06/2005	1629.00	26/08/2005	1620.00	21/11/2005	1686.00
10/03/2005	1718.00	03/06/2005	1632.00	29/08/2005	1613.00	22/11/2005	1696.00
11/03/2005	1720.00	06/06/2005	1624.00	30/08/2005	1612.00	23/11/2005	1695.00
14/03/2005	1705.00	07/06/2005	1620.00	31/08/2005	1614.00	24/11/2005	1697.00
15/03/2005	1720.00	08/06/2005	1634.00	01/09/2005	1625.00	25/11/2005	1694.00
16/03/2005	1716.00	09/06/2005	1658.00	02/09/2005	1630.00	28/11/2005	1699.00
17/03/2005	1708.00	10/06/2005	1658.00	05/09/2005	1618.00	29/11/2005	1670.00
18/03/2005	1692.00	13/06/2005	1650.00	06/09/2005	1630.00	30/11/2005	1680.00
21/03/2005	1691.00	14/06/2005	1653.00	07/09/2005	1644.00	01/12/2005	1662.00
22/03/2005	1683.00	15/06/2005	1671.00	08/09/2005	1643.00	02/12/2005	1676.00
23/03/2005	1666.00	16/06/2005	1682.00	09/09/2005	1640.00	05/12/2005	1680.00
24/03/2005	1676.00	17/06/2005	1655.00	12/09/2005	1641.00	06/12/2005	1679.00
25/03/2005	1684.00	20/06/2005	1664.00	13/09/2005	1630.00	07/12/2005	1710.00
28/03/2005	1684.00	21/06/2005	1662.00	14/09/2005	1615.00	08/12/2005	1670.00
29/03/2005	1683.00	22/06/2005	1667.00	15/09/2005	1607.00	09/12/2005	1694.00
30/03/2005	1679.00	23/06/2005	1689.00	16/09/2005	1600.00	12/12/2005	1685.00
31/03/2005	1676.00	24/06/2005	1702.00	19/09/2005	1601.00	13/12/2005	1702.00
01/04/2005	1683.00	27/06/2005	1707.00	20/09/2005	1609.00	14/12/2005	1708.00
04/04/2005	1678.00	28/06/2005	1695.00	21/09/2005	1590.00	15/12/2005	1729.00
05/04/2005	1669.00	29/06/2005	1702.00	22/09/2005	1569.00	16/12/2005	1714.00
06/04/2005	1674.00	30/06/2005	1692.00	23/09/2005	1594.00	19/12/2005	1746.00
07/04/2005	1677.00	01/07/2005	1684.00	26/09/2005	1600.00	20/12/2005	1737.00
08/04/2005	1698.00	04/07/2005	1699.00	27/09/2005	1603.00	21/12/2005	1749.00
11/04/2005	1688.00	05/07/2005	1695.00	28/09/2005	1617.00	22/12/2005	1770.00
12/04/2005	1665.00	06/07/2005	1694.00	29/09/2005	1629.00	23/12/2005	1779.00
13/04/2005	1665.00	07/07/2005	1697.00	30/09/2005	1618.00	26/12/2005	1777.00
14/04/2005	1663.00	08/07/2005	1688.00	03/10/2005	1613.00	27/12/2005	1777.00
15/04/2005	1637.00	11/07/2005	1708.00	04/10/2005	1618.00	28/12/2005	1777.00
18/04/2005	1612.00	12/07/2005	1713.00	05/10/2005	1625.00	29/12/2005	1777.00
19/04/2005	1616.00	13/07/2005	1727.00	06/10/2005	1610.00	30/12/2005	1774.00
20/04/2005	1623.00	14/07/2005	1749.00	07/10/2005	1587.00	02/01/2006	1755.00
21/04/2005	1600.00	15/07/2005	1771.00	10/10/2005	1590.00	03/01/2006	1770.00
22/04/2005	1616.00	18/07/2005	1755.00	11/10/2005	1595.00	04/01/2006	1812.00
25/04/2005	1615.00	19/07/2005	1750.00	12/10/2005	1601.00	05/01/2006	1821.00

06/01/2006	1800.00	03/04/2006	1889.00	27/06/2006	1729.00	20/09/2006	1772.00
09/01/2006	1806.00	04/04/2006	1868.00	28/06/2006	1706.00	21/09/2006	1783.00
10/01/2006	1795.00	05/04/2006	1878.00	29/06/2006	1735.00	22/09/2006	1774.00
11/01/2006	1792.00	06/04/2006	1866.00	30/06/2006	1761.00	25/09/2006	1778.00
12/01/2006	1804.00	07/04/2006	1854.00	03/07/2006	1787.00	26/09/2006	1777.00
13/01/2006	1790.00	10/04/2006	1850.00	04/07/2006	1775.00	27/09/2006	1792.00
16/01/2006	1786.00	11/04/2006	1853.00	05/07/2006	1780.00	28/09/2006	1791.00
17/01/2006	1754.00	12/04/2006	1836.00	06/07/2006	1766.00	29/09/2006	1816.00
18/01/2006	1738.00	13/04/2006	1838.00	07/07/2006	1770.00	02/10/2006	1848.00
19/01/2006	1749.00	14/04/2006	1838.00	10/07/2006	1754.00	03/10/2006	1820.00
20/01/2006	1745.00	17/04/2006	1838.00	11/07/2006	1759.00	04/10/2006	1839.00
23/01/2006	1720.00	18/04/2006	1842.00	12/07/2006	1751.00	05/10/2006	1870.00
24/01/2006	1742.00	19/04/2006	1830.00	13/07/2006	1723.00	06/10/2006	1866.00
25/01/2006	1712.00	20/04/2006	1829.00	14/07/2006	1690.00	09/10/2006	1866.00
26/01/2006	1726.00	21/04/2006	1823.00	17/07/2006	1676.00	10/10/2006	1878.00
27/01/2006	1726.00	24/04/2006	1818.00	18/07/2006	1669.00	11/10/2006	1890.00
30/01/2006	1744.00	25/04/2006	1797.00	19/07/2006	1679.00	12/10/2006	1896.00
31/01/2006	1744.00	26/04/2006	1792.00	20/07/2006	1707.00	13/10/2006	1908.00
01/02/2006	1737.00	27/04/2006	1816.00	21/07/2006	1690.00	16/10/2006	1917.00
02/02/2006	1763.00	28/04/2006	1806.00	24/07/2006	1675.00	17/10/2006	1913.00
03/02/2006	1741.00	01/05/2006	1791.00	25/07/2006	1704.00	18/10/2006	1895.00
06/02/2006	1742.00	02/05/2006	1800.00	26/07/2006	1708.00	19/10/2006	1877.00
07/02/2006	1741.00	03/05/2006	1815.00	27/07/2006	1726.00	20/10/2006	1875.00
08/02/2006	1745.00	04/05/2006	1818.00	28/07/2006	1732.00	23/10/2006	1873.00
09/02/2006	1751.00	05/05/2006	1829.00	31/07/2006	1749.00	24/10/2006	1875.00
10/02/2006	1782.00	08/05/2006	1849.00	01/08/2006	1748.00	25/10/2006	1870.00
13/02/2006	1775.00	09/05/2006	1830.00	02/08/2006	1726.00	26/10/2006	1883.00
14/02/2006	1780.00	10/05/2006	1829.00	03/08/2006	1722.50	27/10/2006	1865.00
15/02/2006	1778.00	11/05/2006	1817.00	04/08/2006	1719.00	30/10/2006	1853.00
16/02/2006	1778.00	12/05/2006	1792.00	07/08/2006	1724.00	31/10/2006	1859.00
17/02/2006	1775.00	15/05/2006	1745.00	08/08/2006	1738.00	01/11/2006	1869.00
20/02/2006	1785.00	16/05/2006	1733.00	09/08/2006	1735.00	02/11/2006	1874.00
21/02/2006	1796.00	17/05/2006	1745.00	10/08/2006	1725.00	03/11/2006	1870.00
22/02/2006	1781.00	18/05/2006	1685.00	11/08/2006	1748.00	06/11/2006	1874.00
23/02/2006	1813.00	19/05/2006	1687.00	14/08/2006	1750.00	07/11/2006	1884.00
24/02/2006	1849.00	22/05/2006	1692.00	15/08/2006	1760.00	08/11/2006	1882.00
27/02/2006	1894.00	23/05/2006	1685.00	16/08/2006	1764.00	09/11/2006	1894.00
28/02/2006	1941.00	24/05/2006	1692.00	17/08/2006	1762.00	10/11/2006	1875.00
01/03/2006	1926.00	25/05/2006	1695.00	18/08/2006	1770.00	13/11/2006	1875.00
02/03/2006	1939.00	26/05/2006	1706.00	21/08/2006	1763.00	14/11/2006	1874.00
03/03/2006	1922.00	29/05/2006	1737.00	22/08/2006	1766.00	15/11/2006	1878.00
06/03/2006	1912.00	30/05/2006	1730.00	23/08/2006	1779.00	16/11/2006	1880.00
07/03/2006	1910.00	31/05/2006	1684.00	24/08/2006	1772.00	17/11/2006	1902.00
08/03/2006	1859.00	01/06/2006	1724.00	25/08/2006	1773.00	20/11/2006	1896.00
09/03/2006	1869.00	02/06/2006	1780.00	28/08/2006	1762.00	21/11/2006	1896.00
10/03/2006	1841.00	05/06/2006	1783.00	29/08/2006	1775.00	22/11/2006	1890.00
13/03/2006	1863.00	06/06/2006	1760.00	30/08/2006	1781.00	23/11/2006	1886.00
14/03/2006	1860.00	07/06/2006	1771.00	31/08/2006	1800.00	24/11/2006	1870.00
15/03/2006	1857.00	08/06/2006	1739.00	01/09/2006	1794.00	27/11/2006	1867.00
16/03/2006	1856.00	09/06/2006	1752.00	04/09/2006	1793.00	28/11/2006	1852.00
17/03/2006	1869.00	12/06/2006	1785.00	05/09/2006	1813.00	29/11/2006	1858.00
20/03/2006	1860.00	13/06/2006	1730.00	06/09/2006	1809.00	30/11/2006	1867.00
21/03/2006	1846.00	14/06/2006	1719.00	07/09/2006	1799.00	01/12/2006	1853.00
22/03/2006	1835.00	15/06/2006	1706.00	08/09/2006	1793.00	04/12/2006	1838.00
23/03/2006	1860.00	16/06/2006	1754.00	11/09/2006	1782.00	05/12/2006	1847.00
24/03/2006	1850.00	19/06/2006	1755.00	12/09/2006	1794.00	06/12/2006	1878.00
27/03/2006	1873.00	20/06/2006	1728.00	13/09/2006	1817.00	07/12/2006	1918.00
28/03/2006	1841.00	21/06/2006	1741.00	14/09/2006	1806.00	08/12/2006	1945.00
29/03/2006	1842.00	22/06/2006	1758.00	15/09/2006	1805.00	11/12/2006	1975.00
30/03/2006	1895.00	23/06/2006	1727.00	18/09/2006	1810.00	12/12/2006	1974.00
31/03/2006	1892.00	26/06/2006	1731.00	19/09/2006	1799.00	13/12/2006	1987.00

14/12/2006	1997.00	11/01/2007	2075.00	08/02/2007	2070.00	08/03/2007	2107.00
15/12/2006	1990.00	12/01/2007	2069.00	09/02/2007	2081.00	09/03/2007	2110.00
18/12/2006	2000.00	15/01/2007	2075.00	12/02/2007	2054.00	12/03/2007	2128.00
19/12/2006	1985.00	16/01/2007	2050.00	13/02/2007	2061.00	13/03/2007	2099.00
20/12/2006	1992.00	17/01/2007	2015.00	14/02/2007	2072.00	14/03/2007	1995.00
21/12/2006	1975.00	18/01/2007	2035.00	15/02/2007	2089.00	15/03/2007	1990.00
22/12/2006	1962.00	19/01/2007	2015.00	16/02/2007	2102.00	16/03/2007	1982.00
25/12/2006	1970.00	22/01/2007	2054.00	19/02/2007	2118.00	19/03/2007	1991.00
26/12/2006	1970.00	23/01/2007	2039.00	20/02/2007	2134.00	20/03/2007	1968.00
27/12/2006	1984.00	24/01/2007	2057.00	21/02/2007	2151.00	21/03/2007	2012.00
28/12/2006	2004.00	25/01/2007	2102.00	22/02/2007	2127.00	22/03/2007	2062.00
29/12/2006	1988.00	26/01/2007	2075.00	23/02/2007	2119.00	23/03/2007	2064.00
01/01/2007	1993.00	29/01/2007	2061.00	26/02/2007	2119.00	26/03/2007	2043.00
02/01/2007	1999.00	30/01/2007	2062.00	27/02/2007	2095.00	27/03/2007	2036.00
03/01/2007	2042.00	31/01/2007	2057.00	28/02/2007	2036.00	28/03/2007	1996.00
04/01/2007	2062.00	01/02/2007	2060.00	01/03/2007	2044.00	29/03/2007	1999.00
05/01/2007	2071.00	02/02/2007	2053.00	02/03/2007	2099.00	30/03/2007	2007.00
08/01/2007	2073.00	05/02/2007	2055.00	05/03/2007	2036.00		
09/01/2007	2089.00	06/02/2007	2053.00	06/03/2007	2095.00		
10/01/2007	2073.00	07/02/2007	2065.00	07/03/2007	2120.00		

Appendix C.4: *The historic open share prices of Barclays Bank covers the period from 1st July 2002 until 12th September 2008.*

Date	**Prices**	16/09/2002	435.00	03/12/2002	434.50	19/02/2003	383.50
01/07/2002	554.00	17/09/2002	445.00	04/12/2002	425.00	20/02/2003	379.00
02/07/2002	554.00	18/09/2002	429.00	05/12/2002	416.00	21/02/2003	376.25
03/07/2002	540.00	19/09/2002	409.00	06/12/2002	415.00	24/02/2003	376.00
04/07/2002	511.50	20/09/2002	395.50	09/12/2002	405.75	25/02/2003	370.00
05/07/2002	510.00	23/09/2002	395.50	10/12/2002	394.00	26/02/2003	365.25
08/07/2002	511.50	24/09/2002	366.50	11/12/2002	390.00	27/02/2003	348.50
09/07/2002	512.50	25/09/2002	351.00	12/12/2002	387.50	28/02/2003	347.50
10/07/2002	494.00	26/09/2002	373.25	13/12/2002	395.00	03/03/2003	369.75
11/07/2002	477.00	27/09/2002	388.75	16/12/2002	371.00	04/03/2003	359.50
12/07/2002	470.00	30/09/2002	384.00	17/12/2002	395.00	05/03/2003	348.00
15/07/2002	454.50	01/10/2002	372.00	18/12/2002	391.00	06/03/2003	344.25
16/07/2002	431.00	02/10/2002	408.00	19/12/2002	379.50	07/03/2003	343.75
17/07/2002	429.00	03/10/2002	404.00	20/12/2002	377.50	10/03/2003	338.00
18/07/2002	475.00	04/10/2002	403.50	23/12/2002	380.00	11/03/2003	329.00
19/07/2002	489.00	07/10/2002	383.00	24/12/2002	377.75	12/03/2003	331.00
22/07/2002	456.00	08/10/2002	401.75	25/12/2002	381.00	13/03/2003	318.00
23/07/2002	455.50	09/10/2002	399.50	26/12/2002	381.00	14/03/2003	342.50
24/07/2002	430.00	10/10/2002	372.00	27/12/2002	386.25	17/03/2003	342.00
25/07/2002	440.00	11/10/2002	406.25	30/12/2002	369.00	18/03/2003	373.00
26/07/2002	433.00	14/10/2002	427.00	31/12/2002	377.00	19/03/2003	376.00
29/07/2002	463.50	15/10/2002	424.25	01/01/2003	385.00	20/03/2003	371.75
30/07/2002	494.00	16/10/2002	448.00	02/01/2003	385.75	21/03/2003	378.75
31/07/2002	478.50	17/10/2002	460.00	03/01/2003	394.00	24/03/2003	389.00
01/08/2002	468.00	18/10/2002	482.75	06/01/2003	401.00	25/03/2003	375.00
02/08/2002	444.50	21/10/2002	462.75	07/01/2003	375.75	26/03/2003	377.25
05/08/2002	433.00	22/10/2002	463.75	08/01/2003	375.50	27/03/2003	379.25
06/08/2002	400.00	23/10/2002	471.00	09/01/2003	379.00	28/03/2003	381.75
07/08/2002	446.50	24/10/2002	441.50	10/01/2003	390.75	31/03/2003	365.00
08/08/2002	449.50	25/10/2002	437.50	13/01/2003	401.00	01/04/2003	365.00
09/08/2002	452.00	28/10/2002	442.00	14/01/2003	392.25	02/04/2003	374.00
12/08/2002	461.00	29/10/2002	444.25	15/01/2003	385.75	03/04/2003	394.25
13/08/2002	448.00	30/10/2002	435.50	16/01/2003	375.50	04/04/2003	395.00
14/08/2002	437.00	31/10/2002	435.00	17/01/2003	364.00	07/04/2003	410.00
15/08/2002	446.00	01/11/2002	441.25	20/01/2003	347.00	08/04/2003	405.00
16/08/2002	453.00	04/11/2002	446.00	21/01/2003	347.25	09/04/2003	399.25
19/08/2002	471.00	05/11/2002	455.75	22/01/2003	352.25	10/04/2003	391.75
20/08/2002	470.50	06/11/2002	470.00	23/01/2003	356.50	11/04/2003	400.00
21/08/2002	474.50	07/11/2002	468.00	24/01/2003	352.50	14/04/2003	400.00
22/08/2002	472.00	08/11/2002	450.00	27/01/2003	348.00	15/04/2003	413.25
23/08/2002	476.00	11/11/2002	444.50	28/01/2003	341.00	16/04/2003	405.75
26/08/2002	476.00	12/11/2002	445.00	29/01/2003	333.50	17/04/2003	402.00
27/08/2002	477.00	13/11/2002	441.00	30/01/2003	334.00	18/04/2003	414.00
28/08/2002	470.00	14/11/2002	425.25	31/01/2003	343.75	21/04/2003	414.00
29/08/2002	458.50	15/11/2002	422.25	03/02/2003	366.75	22/04/2003	417.00
30/08/2002	464.00	18/11/2002	430.50	04/02/2003	358.25	23/04/2003	429.75
02/09/2002	456.50	19/11/2002	441.00	05/02/2003	362.00	24/04/2003	432.00
03/09/2002	432.00	20/11/2002	440.00	06/02/2003	363.25	25/04/2003	426.25
04/09/2002	433.00	21/11/2002	446.00	07/02/2003	359.75	28/04/2003	417.75
05/09/2002	433.50	22/11/2002	469.75	10/02/2003	354.25	29/04/2003	448.00
06/09/2002	436.00	25/11/2002	468.50	11/02/2003	343.00	30/04/2003	443.00
09/09/2002	436.00	26/11/2002	446.50	12/02/2003	348.50	01/05/2003	432.00
10/09/2002	435.00	27/11/2002	444.25	13/02/2003	343.50	02/05/2003	421.00
11/09/2002	454.50	28/11/2002	456.75	14/02/2003	373.00	05/05/2003	428.00
12/09/2002	442.50	29/11/2002	460.25	17/02/2003	378.75	06/05/2003	431.50
13/09/2002	437.00	02/12/2002	468.00	18/02/2003	382.75	07/05/2003	426.00

08/05/2003	425.00	01/08/2003	467.50	27/10/2003	508.00	20/01/2004	520.75
09/05/2003	410.00	04/08/2003	459.00	28/10/2003	499.50	21/01/2004	514.42
12/05/2003	412.50	05/08/2003	455.50	29/10/2003	497.00	22/01/2004	520.92
13/05/2003	410.00	06/08/2003	449.00	30/10/2003	494.75	23/01/2004	506.50
14/05/2003	406.50	07/08/2003	465.00	31/10/2003	495.75	26/01/2004	510.00
15/05/2003	416.75	08/08/2003	479.50	03/11/2003	495.25	27/01/2004	505.75
16/05/2003	418.00	11/08/2003	484.00	04/11/2003	494.00	28/01/2004	500.00
19/05/2003	429.00	12/08/2003	486.00	05/11/2003	496.00	29/01/2004	503.31
20/05/2003	418.50	13/08/2003	490.00	06/11/2003	490.00	30/01/2004	498.77
21/05/2003	424.00	14/08/2003	481.00	07/11/2003	497.50	02/02/2004	495.54
22/05/2003	420.00	15/08/2003	482.75	10/11/2003	497.50	03/02/2004	496.00
23/05/2003	415.75	18/08/2003	487.50	11/11/2003	492.00	04/02/2004	494.75
26/05/2003	415.25	19/08/2003	493.25	12/11/2003	496.25	05/02/2004	500.00
27/05/2003	416.75	20/08/2003	483.75	13/11/2003	503.00	06/02/2004	502.00
28/05/2003	420.50	21/08/2003	478.00	14/11/2003	491.25	09/02/2004	509.00
29/05/2003	436.20	22/08/2003	475.00	17/11/2003	485.00	10/02/2004	515.25
30/05/2003	438.00	25/08/2003	471.75	18/11/2003	488.25	11/02/2004	512.00
02/06/2003	438.00	26/08/2003	470.00	19/11/2003	485.25	12/02/2004	509.49
03/06/2003	434.00	27/08/2003	470.50	20/11/2003	490.00	13/02/2004	495.00
04/06/2003	435.25	28/08/2003	476.00	21/11/2003	487.75	16/02/2004	495.75
05/06/2003	435.00	29/08/2003	471.25	24/11/2003	484.75	17/02/2004	494.00
06/06/2003	437.50	01/09/2003	464.00	25/11/2003	505.75	18/02/2004	505.00
09/06/2003	438.00	02/09/2003	468.50	26/11/2003	502.50	19/02/2004	503.00
10/06/2003	437.50	03/09/2003	465.25	27/11/2003	513.00	20/02/2004	506.75
11/06/2003	442.00	04/09/2003	469.25	28/11/2003	510.00	23/02/2004	510.25
12/06/2003	451.50	05/09/2003	473.00	01/12/2003	515.00	24/02/2004	506.25
13/06/2003	467.75	08/09/2003	468.25	02/12/2003	520.00	25/02/2004	495.00
16/06/2003	458.25	09/09/2003	471.00	03/12/2003	501.00	26/02/2004	493.75
17/06/2003	465.75	10/09/2003	472.00	04/12/2003	507.00	27/02/2004	492.00
18/06/2003	467.75	11/09/2003	465.25	05/12/2003	500.72	01/03/2004	489.50
19/06/2003	476.00	12/09/2003	469.25	08/12/2003	495.75	02/03/2004	491.50
20/06/2003	462.00	15/09/2003	485.50	09/12/2003	498.25	03/03/2004	488.50
23/06/2003	460.00	16/09/2003	486.00	10/12/2003	492.50	04/03/2004	492.75
24/06/2003	452.75	17/09/2003	499.50	11/12/2003	478.31	05/03/2004	495.50
25/06/2003	454.00	18/09/2003	496.75	12/12/2003	478.66	08/03/2004	501.00
26/06/2003	454.75	19/09/2003	503.00	15/12/2003	483.00	09/03/2004	493.00
27/06/2003	454.50	22/09/2003	485.00	16/12/2003	478.75	10/03/2004	498.50
30/06/2003	458.00	23/09/2003	497.00	17/12/2003	486.23	11/03/2004	498.00
01/07/2003	438.00	24/09/2003	493.75	18/12/2003	487.75	12/03/2004	483.25
02/07/2003	444.25	25/09/2003	478.75	19/12/2003	491.78	15/03/2004	487.25
03/07/2003	447.50	26/09/2003	477.25	22/12/2003	491.35	16/03/2004	482.25
04/07/2003	444.75	29/09/2003	469.00	23/12/2003	494.75	17/03/2004	485.00
07/07/2003	445.75	30/09/2003	470.00	24/12/2003	488.00	18/03/2004	491.50
08/07/2003	457.75	01/10/2003	465.00	25/12/2003	491.25	19/03/2004	487.00
09/07/2003	458.00	02/10/2003	493.00	26/12/2003	491.25	22/03/2004	479.50
10/07/2003	452.75	03/10/2003	494.50	29/12/2003	488.00	23/03/2004	474.75
11/07/2003	447.50	06/10/2003	503.00	30/12/2003	496.00	24/03/2004	476.00
14/07/2003	455.25	07/10/2003	492.00	31/12/2003	497.50	25/03/2004	476.00
15/07/2003	460.00	08/10/2003	498.50	01/01/2004	498.25	26/03/2004	484.50
16/07/2003	465.50	09/10/2003	508.50	02/01/2004	500.00	29/03/2004	482.00
17/07/2003	458.75	10/10/2003	511.00	05/01/2004	504.49	30/03/2004	485.75
18/07/2003	453.00	13/10/2003	514.00	06/01/2004	506.00	31/03/2004	481.25
21/07/2003	454.75	14/10/2003	523.25	07/01/2004	513.00	01/04/2004	479.75
22/07/2003	452.25	15/10/2003	517.00	08/01/2004	512.00	02/04/2004	484.00
23/07/2003	459.00	16/10/2003	516.25	09/01/2004	512.00	05/04/2004	491.50
24/07/2003	463.00	17/10/2003	515.00	12/01/2004	508.50	06/04/2004	493.00
25/07/2003	462.75	20/10/2003	512.75	13/01/2004	514.50	07/04/2004	486.25
28/07/2003	467.25	21/10/2003	522.50	14/01/2004	510.25	08/04/2004	482.00
29/07/2003	469.25	22/10/2003	527.00	15/01/2004	520.50	09/04/2004	486.75
30/07/2003	468.25	23/10/2003	505.00	16/01/2004	530.00	12/04/2004	486.75
31/07/2003	469.00	24/10/2003	505.00	19/01/2004	536.75	13/04/2004	490.50

14/04/2004	488.00	08/07/2004	456.00	01/10/2004	533.50	27/12/2004	583.00
15/04/2004	488.50	09/07/2004	459.25	04/10/2004	550.00	28/12/2004	583.00
16/04/2004	490.00	12/07/2004	458.25	05/10/2004	556.50	29/12/2004	582.00
19/04/2004	490.75	13/07/2004	453.75	06/10/2004	564.00	30/12/2004	585.00
20/04/2004	501.00	14/07/2004	455.00	07/10/2004	560.50	31/12/2004	588.50
21/04/2004	503.75	15/07/2004	456.25	08/10/2004	558.00	03/01/2005	586.00
22/04/2004	503.25	16/07/2004	448.75	11/10/2004	570.00	04/01/2005	584.00
23/04/2004	510.50	19/07/2004	445.75	12/10/2004	577.50	05/01/2005	588.00
26/04/2004	511.00	20/07/2004	442.50	13/10/2004	566.50	06/01/2005	592.50
27/04/2004	511.50	21/07/2004	450.50	14/10/2004	556.00	07/01/2005	586.50
28/04/2004	512.00	22/07/2004	454.25	15/10/2004	554.50	10/01/2005	606.00
29/04/2004	505.25	23/07/2004	448.00	18/10/2004	552.50	11/01/2005	606.00
30/04/2004	506.00	26/07/2004	450.00	19/10/2004	552.50	12/01/2005	593.50
03/05/2004	508.50	27/07/2004	444.00	20/10/2004	552.50	13/01/2005	591.00
04/05/2004	510.00	28/07/2004	455.75	21/10/2004	553.50	14/01/2005	589.00
05/05/2004	505.00	29/07/2004	462.25	22/10/2004	546.00	17/01/2005	597.00
06/05/2004	514.00	30/07/2004	469.00	25/10/2004	537.00	18/01/2005	592.50
07/05/2004	504.50	02/08/2004	456.50	26/10/2004	536.50	19/01/2005	589.00
10/05/2004	490.00	03/08/2004	465.75	27/10/2004	543.50	20/01/2005	585.00
11/05/2004	492.00	04/08/2004	459.75	28/10/2004	544.50	21/01/2005	588.00
12/05/2004	501.00	05/08/2004	474.00	29/10/2004	544.00	24/01/2005	582.00
13/05/2004	503.00	06/08/2004	476.00	01/11/2004	535.00	25/01/2005	579.00
14/05/2004	499.00	09/08/2004	502.00	02/11/2004	545.00	26/01/2005	586.00
17/05/2004	491.50	10/08/2004	501.00	03/11/2004	555.00	27/01/2005	574.00
18/05/2004	495.25	11/08/2004	515.00	04/11/2004	552.50	28/01/2005	581.00
19/05/2004	492.00	12/08/2004	511.00	05/11/2004	559.50	31/01/2005	577.00
20/05/2004	503.25	13/08/2004	512.25	08/11/2004	561.00	01/02/2005	582.50
21/05/2004	500.50	16/08/2004	512.50	09/11/2004	560.00	02/02/2005	599.00
24/05/2004	503.75	17/08/2004	519.00	10/11/2004	560.50	03/02/2005	595.50
25/05/2004	497.00	18/08/2004	517.00	11/11/2004	564.50	04/02/2005	598.00
26/05/2004	502.25	19/08/2004	514.50	12/11/2004	573.50	07/02/2005	600.00
27/05/2004	490.00	20/08/2004	502.25	15/11/2004	568.50	08/02/2005	592.00
28/05/2004	482.00	23/08/2004	509.00	16/11/2004	572.00	09/02/2005	595.00
31/05/2004	475.50	24/08/2004	509.25	17/11/2004	568.00	10/02/2005	582.50
01/06/2004	486.75	25/08/2004	518.50	18/11/2004	575.00	11/02/2005	593.00
02/06/2004	481.00	26/08/2004	525.00	19/11/2004	574.50	14/02/2005	604.50
03/06/2004	480.00	27/08/2004	517.50	22/11/2004	565.50	15/02/2005	606.50
04/06/2004	481.00	30/08/2004	519.75	23/11/2004	565.00	16/02/2005	611.50
07/06/2004	486.25	31/08/2004	518.00	24/11/2004	568.00	17/02/2005	605.00
08/06/2004	488.75	01/09/2004	518.00	25/11/2004	550.00	18/02/2005	606.50
09/06/2004	491.50	02/09/2004	522.25	26/11/2004	540.50	21/02/2005	615.50
10/06/2004	488.75	03/09/2004	520.00	29/11/2004	543.00	22/02/2005	611.50
11/06/2004	490.25	06/09/2004	527.50	30/11/2004	547.00	23/02/2005	589.00
14/06/2004	489.50	07/09/2004	532.50	01/12/2004	540.50	24/02/2005	583.50
15/06/2004	484.50	08/09/2004	526.00	02/12/2004	556.00	25/02/2005	576.50
16/06/2004	481.00	09/09/2004	525.50	03/12/2004	554.50	28/02/2005	572.00
17/06/2004	485.50	10/09/2004	529.25	06/12/2004	555.00	01/03/2005	568.00
18/06/2004	486.25	13/09/2004	535.50	07/12/2004	550.50	02/03/2005	574.00
21/06/2004	487.00	14/09/2004	532.50	08/12/2004	541.00	03/03/2005	565.00
22/06/2004	487.50	15/09/2004	533.50	09/12/2004	548.50	04/03/2005	570.00
23/06/2004	483.50	16/09/2004	535.00	10/12/2004	553.50	07/03/2005	573.50
24/06/2004	483.00	17/09/2004	534.00	13/12/2004	555.50	08/03/2005	566.50
25/06/2004	478.00	20/09/2004	528.50	14/12/2004	569.00	09/03/2005	562.00
28/06/2004	472.00	21/09/2004	531.00	15/12/2004	563.00	10/03/2005	564.50
29/06/2004	476.75	22/09/2004	539.00	16/12/2004	572.50	11/03/2005	567.00
30/06/2004	478.00	23/09/2004	544.00	17/12/2004	578.00	14/03/2005	568.00
01/07/2004	472.00	24/09/2004	522.00	20/12/2004	570.50	15/03/2005	562.50
02/07/2004	471.00	27/09/2004	539.00	21/12/2004	572.00	16/03/2005	570.00
05/07/2004	464.00	28/09/2004	530.00	22/12/2004	573.00	17/03/2005	563.00
06/07/2004	466.00	29/09/2004	534.00	23/12/2004	578.50	18/03/2005	551.50
07/07/2004	460.75	30/09/2004	541.00	24/12/2004	584.00	21/03/2005	547.50

22/03/2005	545.50	15/06/2005	534.50	08/09/2005	574.50	02/12/2005	604.00
23/03/2005	540.50	16/06/2005	533.50	09/09/2005	569.50	05/12/2005	602.50
24/03/2005	545.00	17/06/2005	531.00	12/09/2005	575.50	06/12/2005	596.50
25/03/2005	551.00	20/06/2005	538.00	13/09/2005	569.00	07/12/2005	600.00
28/03/2005	551.00	21/06/2005	535.00	14/09/2005	573.00	08/12/2005	600.00
29/03/2005	548.00	22/06/2005	542.00	15/09/2005	566.00	09/12/2005	600.00
30/03/2005	547.00	23/06/2005	552.00	16/09/2005	562.00	12/12/2005	598.50
31/03/2005	546.00	24/06/2005	560.00	19/09/2005	562.50	13/12/2005	597.00
01/04/2005	543.50	27/06/2005	553.00	20/09/2005	567.50	14/12/2005	598.50
04/04/2005	550.00	28/06/2005	550.00	21/09/2005	567.00	15/12/2005	601.50
05/04/2005	549.00	29/06/2005	559.00	22/09/2005	561.50	16/12/2005	597.00
06/04/2005	551.00	30/06/2005	552.00	23/09/2005	565.50	19/12/2005	600.50
07/04/2005	552.50	01/07/2005	557.50	26/09/2005	571.00	20/12/2005	599.00
08/04/2005	555.50	04/07/2005	563.50	27/09/2005	569.50	21/12/2005	604.50
11/04/2005	555.00	05/07/2005	558.00	28/09/2005	569.50	22/12/2005	609.00
12/04/2005	554.00	06/07/2005	560.00	29/09/2005	577.50	23/12/2005	613.00
13/04/2005	555.00	07/07/2005	559.50	30/09/2005	579.00	26/12/2005	613.00
14/04/2005	558.50	08/07/2005	554.50	03/10/2005	576.00	27/12/2005	613.00
15/04/2005	565.00	11/07/2005	562.00	04/10/2005	586.50	28/12/2005	613.00
18/04/2005	548.00	12/07/2005	559.50	05/10/2005	582.00	29/12/2005	617.00
19/04/2005	550.50	13/07/2005	563.00	06/10/2005	571.00	30/12/2005	613.00
20/04/2005	560.00	14/07/2005	572.00	07/10/2005	565.50	02/01/2006	611.00
21/04/2005	549.00	15/07/2005	579.50	10/10/2005	562.00	03/01/2006	616.50
22/04/2005	556.50	18/07/2005	577.50	11/10/2005	565.50	04/01/2006	623.00
25/04/2005	553.00	19/07/2005	571.00	12/10/2005	563.50	05/01/2006	627.00
26/04/2005	557.50	20/07/2005	568.00	13/10/2005	557.00	06/01/2006	623.00
27/04/2005	548.00	21/07/2005	567.00	14/10/2005	550.00	09/01/2006	630.00
28/04/2005	542.00	22/07/2005	563.00	17/10/2005	552.00	10/01/2006	626.00
29/04/2005	532.00	25/07/2005	566.00	18/10/2005	545.50	11/01/2006	624.50
02/05/2005	537.00	26/07/2005	558.50	19/10/2005	535.00	12/01/2006	626.50
03/05/2005	542.00	27/07/2005	561.00	20/10/2005	539.00	13/01/2006	627.50
04/05/2005	546.00	28/07/2005	566.00	21/10/2005	536.00	16/01/2006	621.00
05/05/2005	549.50	29/07/2005	568.00	24/10/2005	542.50	17/01/2006	619.00
06/05/2005	547.00	01/08/2005	560.00	25/10/2005	551.50	18/01/2006	602.50
09/05/2005	553.50	02/08/2005	560.00	26/10/2005	551.50	19/01/2006	605.00
10/05/2005	554.50	03/08/2005	562.00	27/10/2005	551.50	20/01/2006	604.50
11/05/2005	542.50	04/08/2005	558.00	28/10/2005	546.00	23/01/2006	593.00
12/05/2005	537.00	05/08/2005	579.00	31/10/2005	549.00	24/01/2006	597.00
13/05/2005	539.00	08/08/2005	580.50	01/11/2005	560.00	25/01/2006	592.00
16/05/2005	538.00	09/08/2005	580.50	02/11/2005	565.00	26/01/2006	590.00
17/05/2005	539.00	10/08/2005	586.50	03/11/2005	576.00	27/01/2006	608.00
18/05/2005	541.00	11/08/2005	589.00	04/11/2005	581.00	30/01/2006	612.50
19/05/2005	545.50	12/08/2005	586.00	07/11/2005	581.50	31/01/2006	600.50
20/05/2005	546.00	15/08/2005	577.50	08/11/2005	590.00	01/02/2006	601.00
23/05/2005	545.50	16/08/2005	580.00	09/11/2005	583.50	02/02/2006	618.50
24/05/2005	545.00	17/08/2005	566.50	10/11/2005	584.00	03/02/2006	614.00
25/05/2005	546.50	18/08/2005	566.50	11/11/2005	592.50	06/02/2006	617.00
26/05/2005	530.00	19/08/2005	558.00	14/11/2005	593.00	07/02/2006	619.50
27/05/2005	528.00	22/08/2005	561.50	15/11/2005	599.00	08/02/2006	618.50
30/05/2005	522.00	23/08/2005	559.50	16/11/2005	603.00	09/02/2006	624.50
31/05/2005	525.50	24/08/2005	558.00	17/11/2005	595.50	10/02/2006	634.00
01/06/2005	523.50	25/08/2005	554.00	18/11/2005	605.00	13/02/2006	646.00
02/06/2005	527.00	26/08/2005	557.50	21/11/2005	615.00	14/02/2006	654.00
03/06/2005	529.00	29/08/2005	550.00	22/11/2005	608.00	15/02/2006	656.50
06/06/2005	520.00	30/08/2005	555.00	23/11/2005	608.00	16/02/2006	653.50
07/06/2005	521.00	31/08/2005	554.00	24/11/2005	613.00	17/02/2006	655.00
08/06/2005	524.00	01/09/2005	556.00	25/11/2005	608.00	20/02/2006	654.50
09/06/2005	521.00	02/09/2005	557.50	28/11/2005	606.50	21/02/2006	645.00
10/06/2005	523.00	05/09/2005	559.00	29/11/2005	588.50	22/02/2006	644.00
13/06/2005	529.50	06/09/2005	562.00	30/11/2005	595.50	23/02/2006	664.50
14/06/2005	529.00	07/09/2005	571.00	01/12/2005	592.50	24/02/2006	668.00

27/02/2006	677.00	23/05/2006	599.50	16/08/2006	649.00	09/11/2006	717.50
28/02/2006	673.50	24/05/2006	605.00	17/08/2006	653.00	10/11/2006	711.00
01/03/2006	654.50	25/05/2006	599.00	18/08/2006	655.00	13/11/2006	709.50
02/03/2006	658.00	26/05/2006	609.00	21/08/2006	652.00	14/11/2006	706.50
03/03/2006	653.00	29/05/2006	611.50	22/08/2006	650.00	15/11/2006	706.50
06/03/2006	658.50	30/05/2006	609.00	23/08/2006	649.00	16/11/2006	707.00
07/03/2006	653.00	31/05/2006	584.00	24/08/2006	646.00	17/11/2006	708.00
08/03/2006	654.00	01/06/2006	618.00	25/08/2006	648.00	20/11/2006	707.00
09/03/2006	650.00	02/06/2006	627.00	28/08/2006	649.50	21/11/2006	707.50
10/03/2006	646.00	05/06/2006	626.50	29/08/2006	654.00	22/11/2006	708.00
13/03/2006	664.00	06/06/2006	610.50	30/08/2006	662.50	23/11/2006	702.50
14/03/2006	666.50	07/06/2006	607.00	31/08/2006	663.50	24/11/2006	696.00
15/03/2006	674.50	08/06/2006	601.50	01/09/2006	661.50	27/11/2006	692.50
16/03/2006	669.00	09/06/2006	607.00	04/09/2006	672.00	28/11/2006	678.50
17/03/2006	671.00	12/06/2006	609.50	05/09/2006	673.00	29/11/2006	685.00
20/03/2006	682.50	13/06/2006	592.50	06/09/2006	670.00	30/11/2006	691.00
21/03/2006	677.00	14/06/2006	594.50	07/09/2006	663.00	01/12/2006	684.00
22/03/2006	671.50	15/06/2006	595.00	08/09/2006	658.00	04/12/2006	676.50
23/03/2006	683.50	16/06/2006	605.00	11/09/2006	656.50	05/12/2006	677.00
24/03/2006	683.50	19/06/2006	604.50	12/09/2006	666.00	06/12/2006	677.50
27/03/2006	683.50	20/06/2006	602.00	13/09/2006	677.00	07/12/2006	684.00
28/03/2006	674.50	21/06/2006	605.00	14/09/2006	675.00	08/12/2006	712.00
29/03/2006	669.00	22/06/2006	606.50	15/09/2006	677.50	11/12/2006	724.00
30/03/2006	675.00	23/06/2006	601.00	18/09/2006	679.50	12/12/2006	721.00
31/03/2006	677.50	26/06/2006	599.50	19/09/2006	671.00	13/12/2006	717.50
03/04/2006	681.00	27/06/2006	603.00	20/09/2006	663.00	14/12/2006	719.00
04/04/2006	671.50	28/06/2006	589.50	21/09/2006	669.00	15/12/2006	722.00
05/04/2006	672.50	29/06/2006	599.50	22/09/2006	666.50	18/12/2006	727.50
06/04/2006	679.50	30/06/2006	620.00	25/09/2006	665.00	19/12/2006	721.50
07/04/2006	686.00	03/07/2006	618.00	26/09/2006	663.00	20/12/2006	720.50
10/04/2006	697.50	04/07/2006	623.00	27/09/2006	667.00	21/12/2006	720.00
11/04/2006	698.50	05/07/2006	620.50	28/09/2006	664.00	22/12/2006	725.00
12/04/2006	680.50	06/07/2006	621.00	29/09/2006	671.50	25/12/2006	729.50
13/04/2006	683.00	07/07/2006	623.00	02/10/2006	682.50	26/12/2006	729.50
14/04/2006	683.00	10/07/2006	627.50	03/10/2006	681.00	27/12/2006	735.00
17/04/2006	683.00	11/07/2006	615.50	04/10/2006	684.00	28/12/2006	739.00
18/04/2006	679.50	12/07/2006	611.50	05/10/2006	695.00	29/12/2006	733.50
19/04/2006	677.00	13/07/2006	603.00	06/10/2006	689.50	01/01/2007	730.00
20/04/2006	681.00	14/07/2006	587.00	09/10/2006	697.00	02/01/2007	737.00
21/04/2006	679.00	17/07/2006	590.00	10/10/2006	707.00	03/01/2007	748.00
24/04/2006	676.00	18/07/2006	585.50	11/10/2006	707.50	04/01/2007	755.00
25/04/2006	675.50	19/07/2006	597.00	12/10/2006	710.00	05/01/2007	756.50
26/04/2006	685.00	20/07/2006	613.00	13/10/2006	719.00	08/01/2007	752.00
27/04/2006	684.00	21/07/2006	603.50	16/10/2006	722.00	09/01/2007	756.00
28/04/2006	682.00	24/07/2006	599.50	17/10/2006	718.50	10/01/2007	761.00
01/05/2006	685.00	25/07/2006	615.50	18/10/2006	710.00	11/01/2007	757.50
02/05/2006	682.50	26/07/2006	611.50	19/10/2006	714.00	12/01/2007	760.00
03/05/2006	689.50	27/07/2006	618.50	20/10/2006	713.50	15/01/2007	765.00
04/05/2006	679.50	28/07/2006	625.00	23/10/2006	715.00	16/01/2007	766.00
05/05/2006	680.50	31/07/2006	638.00	24/10/2006	715.00	17/01/2007	754.00
08/05/2006	684.00	01/08/2006	631.50	25/10/2006	715.00	18/01/2007	749.00
09/05/2006	679.50	02/08/2006	625.50	26/10/2006	714.50	19/01/2007	747.00
10/05/2006	675.50	03/08/2006	627.50	27/10/2006	710.50	22/01/2007	749.00
11/05/2006	666.50	04/08/2006	622.50	30/10/2006	702.50	23/01/2007	746.00
12/05/2006	655.50	07/08/2006	630.00	31/10/2006	702.00	24/01/2007	746.00
15/05/2006	639.50	08/08/2006	633.00	01/11/2006	709.00	25/01/2007	760.00
16/05/2006	635.00	09/08/2006	637.00	02/11/2006	703.50	26/01/2007	753.50
17/05/2006	640.00	10/08/2006	638.00	03/11/2006	699.50	29/01/2007	743.50
18/05/2006	616.50	11/08/2006	636.00	06/11/2006	697.50	30/01/2007	751.00
19/05/2006	611.50	14/08/2006	643.50	07/11/2006	706.00	31/01/2007	751.00
22/05/2006	612.00	15/08/2006	647.50	08/11/2006	714.50	01/02/2007	747.50

02/02/2007	751.00	30/04/2007	723.00	24/07/2007	739.50	17/10/2007	617.00
05/02/2007	756.50	01/05/2007	729.50	25/07/2007	732.50	18/10/2007	624.00
06/02/2007	753.50	02/05/2007	720.50	26/07/2007	714.50	19/10/2007	596.50
07/02/2007	762.50	03/05/2007	725.50	27/07/2007	686.00	22/10/2007	578.00
08/02/2007	759.00	04/05/2007	752.00	30/07/2007	686.00	23/10/2007	589.50
09/02/2007	769.00	07/05/2007	732.50	31/07/2007	691.00	24/10/2007	591.00
12/02/2007	770.00	08/05/2007	733.00	01/08/2007	685.00	25/10/2007	591.00
13/02/2007	770.00	09/05/2007	727.00	02/08/2007	690.00	26/10/2007	586.00
14/02/2007	781.00	10/05/2007	723.50	03/08/2007	689.50	29/10/2007	597.50
15/02/2007	781.00	11/05/2007	710.00	06/08/2007	670.00	30/10/2007	588.00
16/02/2007	780.50	14/05/2007	721.00	07/08/2007	691.00	31/10/2007	596.50
19/02/2007	785.00	15/05/2007	716.50	08/08/2007	705.00	01/11/2007	595.00
20/02/2007	775.00	16/05/2007	716.00	09/08/2007	703.00	02/11/2007	563.50
21/02/2007	790.00	17/05/2007	717.00	10/08/2007	670.00	05/11/2007	531.00
22/02/2007	786.50	18/05/2007	718.50	13/08/2007	655.00	06/11/2007	530.00
23/02/2007	785.00	21/05/2007	730.50	14/08/2007	650.00	07/11/2007	527.50
26/02/2007	793.00	22/05/2007	725.00	15/08/2007	621.00	08/11/2007	495.00
27/02/2007	783.00	23/05/2007	720.00	16/08/2007	620.00	09/11/2007	491.00
28/02/2007	758.00	24/05/2007	714.50	17/08/2007	601.50	12/11/2007	485.00
01/03/2007	739.00	25/05/2007	712.00	20/08/2007	635.00	13/11/2007	510.00
02/03/2007	730.00	28/05/2007	720.00	21/08/2007	639.00	14/11/2007	550.00
05/03/2007	705.00	29/05/2007	728.00	22/08/2007	633.00	15/11/2007	563.00
06/03/2007	715.00	30/05/2007	726.50	23/08/2007	644.00	16/11/2007	521.50
07/03/2007	717.00	31/05/2007	731.00	24/08/2007	624.00	19/11/2007	514.00
08/03/2007	721.00	01/06/2007	722.00	27/08/2007	611.00	20/11/2007	496.00
09/03/2007	729.00	04/06/2007	729.00	28/08/2007	603.00	21/11/2007	500.00
12/03/2007	739.00	05/06/2007	735.50	29/08/2007	599.00	22/11/2007	490.50
13/03/2007	730.00	06/06/2007	736.00	30/08/2007	607.50	23/11/2007	490.50
14/03/2007	688.00	07/06/2007	738.00	31/08/2007	607.50	26/11/2007	520.00
15/03/2007	687.00	08/06/2007	719.00	03/09/2007	620.00	27/11/2007	494.50
16/03/2007	683.00	11/06/2007	731.00	04/09/2007	639.50	28/11/2007	533.00
19/03/2007	692.00	12/06/2007	735.00	05/09/2007	637.00	29/11/2007	561.00
20/03/2007	677.50	13/06/2007	728.00	06/09/2007	626.00	30/11/2007	542.00
21/03/2007	712.00	14/06/2007	738.00	07/09/2007	605.00	03/12/2007	569.50
22/03/2007	721.50	15/06/2007	741.00	10/09/2007	584.00	04/12/2007	563.00
23/03/2007	740.00	18/06/2007	764.00	11/09/2007	588.00	05/12/2007	542.00
26/03/2007	754.00	19/06/2007	750.00	12/09/2007	608.00	06/12/2007	578.00
27/03/2007	747.50	20/06/2007	747.00	13/09/2007	609.00	07/12/2007	561.00
28/03/2007	722.50	21/06/2007	743.00	14/09/2007	605.00	10/12/2007	559.50
29/03/2007	726.00	22/06/2007	729.00	17/09/2007	593.00	11/12/2007	574.50
30/03/2007	730.00	25/06/2007	712.50	18/09/2007	585.50	12/12/2007	544.00
02/04/2007	722.00	26/06/2007	710.00	19/09/2007	640.00	13/12/2007	548.50
03/04/2007	731.50	27/06/2007	704.50	20/09/2007	634.00	14/12/2007	526.50
04/04/2007	733.50	28/06/2007	710.50	21/09/2007	623.00	17/12/2007	518.00
05/04/2007	728.00	29/06/2007	700.00	24/09/2007	639.00	18/12/2007	519.50
06/04/2007	733.00	02/07/2007	696.00	25/09/2007	612.00	19/12/2007	501.00
09/04/2007	733.00	03/07/2007	694.00	26/09/2007	603.50	20/12/2007	501.00
10/04/2007	735.50	04/07/2007	696.50	27/09/2007	602.00	21/12/2007	509.00
11/04/2007	736.50	05/07/2007	716.50	28/09/2007	595.50	24/12/2007	512.50
12/04/2007	734.50	06/07/2007	708.50	01/10/2007	593.50	25/12/2007	516.50
13/04/2007	738.00	09/07/2007	723.00	02/10/2007	617.00	26/12/2007	516.50
16/04/2007	758.00	10/07/2007	718.50	03/10/2007	630.00	27/12/2007	514.00
17/04/2007	758.50	11/07/2007	707.50	04/10/2007	637.00	28/12/2007	508.50
18/04/2007	753.00	12/07/2007	707.50	05/10/2007	657.50	31/12/2007	509.00
19/04/2007	741.00	13/07/2007	727.50	08/10/2007	667.00	01/01/2008	504.00
20/04/2007	744.50	16/07/2007	736.00	09/10/2007	665.50	02/01/2008	502.00
23/04/2007	760.00	17/07/2007	733.50	10/10/2007	671.00	03/01/2008	504.50
24/04/2007	737.00	18/07/2007	727.50	11/10/2007	658.00	04/01/2008	505.00
25/04/2007	730.00	19/07/2007	730.00	12/10/2007	642.50	07/01/2008	484.00
26/04/2007	730.00	20/07/2007	729.00	15/10/2007	649.00	08/01/2008	474.75
27/04/2007	723.00	23/07/2007	730.00	16/10/2007	625.50	09/01/2008	468.00

10/01/2008	463.00	04/04/2008	490.00	03/07/2008	280.50
11/01/2008	450.50	07/04/2008	491.00	04/07/2008	293.25
14/01/2008	465.00	08/04/2008	480.00	07/07/2008	282.00
15/01/2008	482.00	09/04/2008	474.00	08/07/2008	276.50
16/01/2008	457.50	10/04/2008	469.00	09/07/2008	288.00
17/01/2008	475.00	11/04/2008	469.00	10/07/2008	283.25
18/01/2008	463.00	14/04/2008	446.00	11/07/2008	284.50
21/01/2008	435.00	15/04/2008	443.75	14/07/2008	273.00
22/01/2008	402.00	16/04/2008	455.50	15/07/2008	262.00
23/01/2008	467.00	17/04/2008	486.50	16/07/2008	264.00
24/01/2008	487.00	18/04/2008	480.00	17/07/2008	288.00
25/01/2008	500.00	21/04/2008	493.00	18/07/2008	280.00
28/01/2008	474.00	22/04/2008	465.00	21/07/2008	320.00
29/01/2008	488.00	23/04/2008	464.00	22/07/2008	314.50
30/01/2008	483.25	24/04/2008	457.00	23/07/2008	325.00
31/01/2008	474.00	25/04/2008	462.50	24/07/2008	357.00
01/02/2008	476.50	28/04/2008	470.75	25/07/2008	335.00
04/02/2008	479.75	29/04/2008	464.00	28/07/2008	355.00
05/02/2008	478.50	30/04/2008	457.00	29/07/2008	315.00
06/02/2008	456.00	01/05/2008	458.00	30/07/2008	335.00
07/02/2008	461.75	02/05/2008	470.75	31/07/2008	335.00
08/02/2008	451.25	06/05/2008	473.00	01/08/2008	332.75
11/02/2008	441.00	07/05/2008	479.50	04/08/2008	343.00
12/02/2008	435.00	08/05/2008	468.00	05/08/2008	344.75
13/02/2008	450.50	09/05/2008	457.25	06/08/2008	374.00
14/02/2008	459.75	12/05/2008	449.00	07/08/2008	360.00
15/02/2008	444.50	13/05/2008	448.25	08/08/2008	365.00
18/02/2008	440.00	14/05/2008	432.25	11/08/2008	365.00
19/02/2008	444.00	15/05/2008	438.00	12/08/2008	377.75
20/02/2008	469.00	16/05/2008	417.50	13/08/2008	370.75
21/02/2008	495.00	19/05/2008	414.50	14/08/2008	349.00
22/02/2008	479.50	20/05/2008	409.50	15/08/2008	349.50
25/02/2008	491.75	21/05/2008	410.00	18/08/2008	347.00
26/02/2008	508.50	22/05/2008	390.00	19/08/2008	335.00
27/02/2008	513.50	23/05/2008	393.50	20/08/2008	313.00
28/02/2008	515.00	27/05/2008	389.75	21/08/2008	312.50
29/02/2008	494.50	28/05/2008	395.00	22/08/2008	310.50
03/03/2008	467.00	29/05/2008	380.50	26/08/2008	320.25
04/03/2008	458.50	30/05/2008	377.50	27/08/2008	323.50
05/03/2008	445.00	02/06/2008	370.25	28/08/2008	332.50
06/03/2008	450.00	03/06/2008	359.50	29/08/2008	351.75
07/03/2008	420.00	04/06/2008	357.00	01/09/2008	350.00
10/03/2008	426.00	05/06/2008	358.75	02/09/2008	356.25
11/03/2008	421.50	06/06/2008	366.50	03/09/2008	355.00
12/03/2008	452.75	10/06/2008	311.50	04/09/2008	350.00
13/03/2008	446.00	11/06/2008	328.00	05/09/2008	322.75
14/03/2008	450.00	12/06/2008	304.25	08/09/2008	359.00
17/03/2008	409.00	13/06/2008	325.00	09/09/2008	356.50
18/03/2008	405.00	16/06/2008	338.50	10/09/2008	361.00
19/03/2008	422.00	17/06/2008	331.25	11/09/2008	344.00
20/03/2008	417.75	18/06/2008	337.00	12/09/2008	343.50
21/03/2008	429.00	19/06/2008	321.50		
24/03/2008	429.00	20/06/2008	318.75		
25/03/2008	478.00	23/06/2008	305.00		
26/03/2008	452.25	24/06/2008	305.00		
27/03/2008	449.00	25/06/2008	328.00		
28/03/2008	460.50	26/06/2008	320.00		
31/03/2008	440.25	27/06/2008	301.25		
01/04/2008	447.00	30/06/2008	298.75		
02/04/2008	485.00	01/07/2008	291.00		
03/04/2008	512.50	02/07/2008	288.75		